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Essays in Transport Economics

By

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Preface

This thesis concludes more than three years of research as a PhD student at the Department of Transport at the Technical University of Denmark. The work in this thesis is part of a large research project, Intelligent Road User Chagrining (called IRUC). Financial support from the Danish Strategic Research Counsel is gratefully acknowledged.

I would like to thank my supervisors Mogens Fosgerau and Katrine Hjorth for their excellent guidance, patience, and being extremely accessible and supportive. Your guidance helped me in all the time of research and writing. Mogens, thank you for sharing me your imaginative research ideas and providing ingenious suggestions that have carried me through during times of great difficulty. Katrine, thank you for answering my endless questions and for being a great office-mate.

I would like to thank DTU Transport for providing excellent atmosphere for doing research. It has been a great pleasure to be part of the institute. I was lucky to have helpful and inspiring colleagues. Thanks to Ismir for your motivation and help with the data; Stefan for his encouragement and support, Gebeyehu for being a great friend, proof reading my papers and for giving me someone to moan at when work was not going according to plan; Abhishek for his support and suggestions; Niken and Jesper for their help with SAS. Spatial thanks to Elisabetta Cherchi for your help with discrete choice models and editorial and research support. I thank Camilla, Karen, Caroline, Marianne Ø, Ulla, Jonni and Marianne B for their excellent administrative assistance.

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I would like to thank the co-authors of my papers: Mogens Fosgerau, Katrine Hjorth, Ismir Mulalic, Jos van Ommeren, Ninette Pilegaard and Jeppe Rich for your encouragement, support and guidance. I have learned a lot from you. Your involvement in my work has greatly improved the quality of this thesis. Thank you.

I would also like to thank my family and friends; you were always supporting me and encouraging me with their best wishes. Finally, I would like to thank my wife, Genet Gebremecaiel. You were always supportive and stood by me through the good time and bad.

Dereje Fentie Abegaz, 2015

Dansk abstrakt

Ph.d.-afhandlingen består af fire selvstændige kapitler inden for det transportøkonomiske område. Kapitlerne omhandler emner som modellering af adfærdsmæssige reaktioner på rejsetidsvariabilitet, måling af omkostningerne i forbindelse med rejsetidsvariabilitet, arbejdsmarkedskonsekvenser som følge af ændrede pendlingsomkostninger og anvendelse af diskretevalg modeller til at undersøge variationer i betalinsvilligheden for rejseinformationssystemer. Det centrale emne, der forbinder kapitlerne, er pendlingsomkostninger. De vigtigste resultater i afhandlingen er følgende:

- Med brug of danske data udfordres den teoretiske ækvivalens mellem to metoder til måling af omkostninger i forbindelse med rejsetidsvariabilitet. Resultaterne fra analysen støtter ikke denne teoretiske ækvivalens (Kapitel 1).
- I en model, hvor to personer pendler til et fælles møde, viser kapitel 2 valget af et optimalt mødetidspunkt og at en forbedret forudsigelighed af rejsetiden er en fordel for begge personer.
- Kapitel 3 omhandler brug af diskretevalg modeller til at undersøge betalinsvilligheden for avancerede rejseinformationssystemer på tværs af individer. Analysen viser, at de begrænsninger der er indbyggede i modellen, kan være afgørende for resultaterne.
- Det påvistes ligeledes, at når en typisk dansk virksomhed flytter 10 km væk, får flytningen 2% af virksomhedens ansatte til at forlade virksomheden inden for en periode på tre år (Kapitel 4).

Introduction and summary

The PhD thesis consists of four self-contained chapters in the area of Transport Economics. The main aim of the thesis is not to produce a single message which is supported by all four chapters. Rather, each chapter is written to make a contribution of its own. The thesis covers a wide range of issues such as modelling behavioural reactions to travel time variability, the measurement of the cost of travel time variability, the labour market implication of changes in commute costs, and the application of discrete choice models to investigate variations in willingness to pay for travel information systems across individuals and the implication of model assumptions on the estimated distribution.

Chapter 1 is titled: "*Testing the slope model of scheduling preferences with stated preference data*", and is a joint work with Katrine Hjorth and Jeppe Rich. This study used a stated preference data to challenge the theoretical equivalence of two methods for measuring the value of travel time variability: the slope model of the scheduling approach (Fosgerau & Engelson, 2011) against its reduced form model. The analysis is based on data from two choice experiments that are identical except one has a fixed departure time while the other allows respondents to choose their optimal departure time. According to the scheduling model, the two experiments yield the same result if travellers can freely choose departure time to maximise utility, and if the distribution of travel times is independent of departure times. It turns out that the empirical results in this paper do not support the theoretical equivalence of the two models as the implied value of travel time variability under the reduced form model is an order of magnitude larger. This finding is robust and is in line with a recent Swedish study by Börjesson *et al.* (2012). Because of data better suited for the analysis, we ruled out some potential explanations lined up by past research for the observed discrepancy between the two models. Although the similarity of results across studies could suggest the presence of a more fundamental problem in estimating the valuation of travel time variability based on data from hypothetical experiments, it is recommended to test the equivalence of the models based on real life data before we can rule out hypothetical bias as a potential explanation for the discrepancy. (*A paper based on this chapter was presented at the 3rd Symposium for the European Association for Research in Transportation, Leeds, UK, 10-12 September, 2014.*)

Chapter 2 is titled "*Valuation of travel time variability with endogenous scheduling* *of a meeting time*", and is a joint work with Mogens Fosgerau. The chapter involves a theoretical model to examine the choice of an optimal meeting time in a situation where individuals can freely choose meeting times. It extends the model of Fosgerau *et al.* (2014) by introducing a notion of a designated meeting time and a penalty that may be imposed when one arrives later than the meeting time. Such a meeting time can be obtained as an agreement outcome in a bargaining process over potential meeting times. The model considers two individuals who choose departure and meeting times in the presence of uncertain travel times for a trip towards a joint meeting. An important feature of the model is the physical property that a meeting starts only when both individuals arrive at the destination. The study shows the existence of a unique optimal meeting time and a unique Nash equilibrium in departure times. It finds that an increase in the variance of the difference between individual travel times is costly for both individuals. It also find that an increase in travel time variance of one person is costly for both. Compared to Fosgerau *et al.* (2014), the introduction of a lateness penalty allows an additional mechanism through which a change in travel time variance of one individual affects the pay-off of both individuals. (*Previous versions of this paper were presented at the 2nd Symposium of the European Association for Research in Transportation, Stockholm, 4-6 Sept, 2013; and at the ITEA's Annual Conference and Summer School on Transportation Economics, Toulouse, 2–6 June, 2014.*)

This paper is related the scheduling model in chapter 1: both models consider scheduling choices in the presence of travel time variability. They differ in two important respects: First, whereas the model in this chapter allows individuals to choose a meeting time, the slope model assumes a fixed arrival time. Moreover, while the slope model takes scheduling choices merely as a personal matter, the model in this chapter allows strategic interaction in scheduling choice. As a result, the slope model does not capture the effect of improved variability of travel times for one person on another.

Chapter 3 is titled:"*Advanced methods make a difference: A case of the distribution of willingness to pay for advanced traveller information systems*". This study is concerned with the use of discrete choice models to estimate the distribution of willingness to pay for advanced traveller information systems and the implication of certain model assumptions on the estimated distribution of willingness to pay. The study uses a flexible estimation method based on data from a stated choice experiment designed to measure the willingness to pay for several types of information that an advanced traveller information system can provide. Different models were estimates that vary in terms of restrictions embodied. While simpler and relatively more advanced models yield nicely dispersed distribution for willingness to pay, this distribution ceased to exist when some restrictions are set free. The less restrictive model fitted the data better, and in this model, which combines the latent class and mixed logit models, it turns out that the data do not reveal any dispersion in the willingness to pay for advanced traveller information systems. Results indicate that a significant share of individuals is unwilling to pay for advanced traveller information systems and that willingness to pay is tightly distributed among those who are willing to pay a positive amount. Findings in this study illustrate the importance of model specification testing, and that results regarding the estimated distribution of willingness to pay can be highly dependent on restrictions built into the model. (*A paper based on this chapter is under review at Transportation Research Part C: Emerging Technologies, and was presented at the 94th Annual Meeting of the Transportation Research Board (TRB), Washington, D.C., 11-14 January 2015.*)

Chapter 4 is titled "*The effect of a firm's relocation distance on worker turnover*", and is a joint work with Ismir Mulalic, Jos van Ommeren and Ninette Pilegaard. Using a matched worker-firm data from Denmark for the years 2000-2007, this study examines whether and how much a firm's relocation distance is related to worker turnover. Firm relocation alters the pattern of commutes to workers: some workers benefit from shortened commutes while other face lengthened commutes. The costs of residential mobility and long distance commuting could induce those whose face lengthened commutes to move jobs. Those who faced longer commutes incur higher commuting costs; and they can minimise these costs by moving residence to shorten commutes or by moving to a nearby job. When the costs of residential mobility and long distance commuting are higher, job mobility becomes a more attractive proposition.

The analysis finds a positive and significant but moderate effect of relocation distance on worker turnover. This effect is robust to the inclusion of firm level characteristics and year and municipality fixed effects. Results in this chapter establish that, on average, a 10 km increase in relocation distance leads to a 2–4 percent increase in the annual rate of worker turnover at the firm level over a period of three years, including the year of relocation. The estimated effect is stronger in the first year after relocation and pales away after the third year as workers more or less fully adjust to the relocation. It is not surprising that we obtained a smaller effect since, first most firms relocated locally. Second, the high rate of job mobility in Denmark means that workers expect to be mobile in the labour market; hence, it may matter less when their firm relocates. Moreover, it is possible that workers knew about the relocation decision and left the firm in the years and months before the relocation. The study also examines whether the distance of relocation captures the effect of changes at the firm because of the relocation. Results indicate that, after controlling for relocation distance, firm relocation has no significant effect on worker turnover.

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CHAPTER 1

Testing the slope model of scheduling preferences on stated preference data*

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Abstract

This paper used a stated preference data to challenge the theoretical equivalence of two methods for measuring the value of travel time variability: the 'slope model' of the scheduling approach against its reduced form model. The analysis is based on data from two choice experiments that are identical except one has a fixed departure time while the other allows respondents to choose their optimal departure time. When departure times are optimally chosen and the distribution of travel times is independent of departure times, the two methods are theoretically equivalent, hence are expected to yield similar results. The empirical results in this paper do not support the theoretical equivalence of the two models as the implied value of travel time variability under the reduced form model is an order of magnitude larger. This finding, which is robust to certain model assumptions, is in line with a recent Swedish study by Böjesson, Eliasson and Franklin. Because of data better suited for the analysis, we ruled out some potential explanations lined up by past research for the observed discrepancy between the two models.

Keywords: travel time variability; value of reliability; the slope model; scheduling preferences

JEL code: R41

*A previous version of this paper was presented at the 3rd Symposium of the European Association for Research in Transportation, Leeds, UK, 10-12 September, 2014.

1 Introduction

Valuation of travel time variability (TTV) or reliability has received much attention in the transport literature in recent years. Most empirical studies measuring preferences for TTV use stated preference (SP) data and apply one of two approaches: The scheduling approach or the reduced form approach, which also referred to as the mean-variance or mean-standard deviation approach or similar. Whereas the scheduling approach infers the valuation of TTV from individuals' preferences against being late or early relative to a desired arrival time, in the reduced form model, the valuation of TTV is directly linked to specific measures of TTV such as the variance or standard deviation of travel times.

Under certain theoretical assumptions, the two approaches can be shown to be equivalent (Fosgerau & Karlstrom, 2010; Fosgerau & Engelson, 2011). However, empirical research reveals that the two approaches could provide very different results (see, e.g. Hollander, 2006; Börjesson *et al.*, 2012), either because the theoretical assumptions do not hold or because the approaches tend to be applied on different types of SP data. Since the transport literature is yet to agree on a preferred method for presenting TTV in SP experiments and measuring preferences, it is important to understand why the approaches differ and possibly point to specific theoretical assumptions that are too restrictive or address specific differences in the SP experiments that have critical impact on the estimates.

In this paper, we compare the two approaches using data from a Danish SP survey aimed at valuing TTV. Our analysis is closely related to a recent paper by Börjesson *et al.* (2012); however, it differs with regard to data: using data better suited for comparing the methods, we can rule out some of the potential explanations for the observed difference between the two methods in their analysis. Because they estimated the scheduling model based on data without TTV, they could not rule out whether this contributed to the observed discrepancy between the two models. The two SP games we designed to estimate the two models are much more similar to each other than the two games used in Börjesson *et al.* (2012): Both our SP games involve TTV and use the same presentation of the distribution of travel times. The only difference between the games is that one includes a departure time attribute, while the other allows respondents to choose their preferred departure time. Compared to Börjesson *et al.* (2012), the similarity between the two SP games narrows down the list of potential factors differentiating the two models.

A further contribution of this paper is that it examines whether the results in

Börjesson *et al.* (2012) who sampled users of scheduled services, namely train and metro, also holds for car commuters. Moreover, we tested different ways of deriving the 'ideal arrival time', a key concept in the scheduling model, from the data to probe if this affects the hypothesised equivalence between scheduling and reduced form models.[1]

Our analysis is based on the form of scheduling model developed by Vickrey (1973) and later analysed by Tseng & Verhoef (2008) and Fosgerau & Engelson (2011). This scheduling model considers journey scheduling choices in the presence of uncertain travel times, in the case where departure time choice is continuous. It assumes that travellers have a specific marginal utility of being at the origin and another marginal utility of being at the destination, and that both marginal utilities vary over time of day, such that at one point in time, t_0, it becomes more desirable to be at the destination than at the origin. Travellers are assumed to choose their departure time optimally by maximising their expected utility, given the distribution of travel time. We denote the relation between expected utility, departure time and the travel time distribution as *the scheduling model*, while *the reduced form model* denotes the relation between the optimal expected utility (assuming optimal departure time) and the travel time distribution.

In line with Fosgerau & Engelson (2011) we assume that the utility rates are simple linear functions of time of day. This yields a simple model, referred to as the 'slope model', which has property that the theoretical cost of TTV is proportional to the variance of travel times.

We use SP data from two different choice experiments (games). Both experiments are from a survey among Danish car drivers commuting to work in the morning and each SP game consists of six binary choices between travel alternatives characterised by a set of attributes. The attributes include a travel time distribution with two possible outcomes and their probabilities of occurrence. In the first SP game, the only attributes are journey cost and the travel time distribution, while the second SP game in addition includes a departure time attribute. We use the first SP game to estimate the parameters of the reduced form model and the second SP game to estimate the preference parameters for the scheduling model.

The empirical analysis in this paper does not support the hypothesised equivalence

[1]The ideal arrival time is a point in time at which it is preferred to be at destination rather than at the origin. Thus, it corresponds to the arrival time in the hypothetical case where travel time is zero with certainty.

between the scheduling and reduced form models. The two methods are shown to yield very different results, as the value of TTV differs by a factor of at least 12, and as much as 48 in some cases. Our result complements Börjesson *et al.* (2012) who suggest three explanations of the discrepancy between scheduling and reduced form models:

- In departure time choices without TTV, information about actual arrival time is given with certainty, so respondents are in principle able to reschedule their activities according to this known outcome, thus changing their preferences for being at the origin/destination at a specific time.
- The scheduling model does not allow for a disutility of uncertainty per se: The only thing that matters is when the respondent departs and arrives, and the uncertainty therefore enters through the expectation of the utility of arriving at a specific time. However, it may be that TTV affects the perception of travel time or the travel situation as such, and thus affects preferences in other ways than through the expectation of the utility of arriving at a specific time.[2]
- Policy bias and focus bias: As in all SP experiments, there is a risk that respondents try to answer the SP questions in a way that they think will cause certain desirable effects – rather than being in accordance with their intrinsic preferences. If this so-called policy bias works differently in the two SP games it may cause a difference between the scheduling and reduced form models. Another source of error in SP experiments is focus bias, which arises when respondents focus on some specific attributes while ignoring or providing less attention to others. The two experiments in Börjesson *et al.* (2012) are quite different, as one is about preferences for departing/arriving at specific times known with certainty and the other is about the risk of delays. The delay attributes (probabilities and durations) may be more complex to interpret and relate to the travellers' own experience, and this may result in a focus bias in the delay experiment.

Since both our SP games involve TTV, the first explanation can be ruled out, albeit only partially since the fixed departure time attribute in one of the SP games provides some scope for rescheduling. Compared to a situation where arrival times are known, a

[2] Börjesson *et al.* (2012) mention three examples of such an effect: 'Anxiety costs' (stemming from the traveller disliking not knowing what is going to happen), 'decision costs' (TTV makes it harder for the traveller to determine his optimal departure time), and 'contingency planning costs' (TTV potentially forces the traveller to develop a contingency plan in case he arrives very late).

fixed departure time offers smaller scope for rescheduling since arrival time is uncertain due to TTV. The second explanation may still apply to some extent, if the disutility of uncertainty per se is captured differently in the two models. However, since both games involve TTV, such an effect is expected to be smaller than in the study by Börjesson *et al.* (2012). The third explanation may also still apply, but only to some degree since the two SP games *are* only slightly different. In any case, it would be expected that the effect is smaller in our case than in the study by Börjesson *et al.* (2012).

To aid future TTV valuation studies (in selecting appropriate methods), it is relevant to discuss another line of explanation, which relates to the appropriateness of the applied scheduling model and the other theoretical assumptions we impose in our analysis. Clearly, if the underlying assumptions in the scheduling model are incorrect, then the derived equivalence between scheduling models and reduced form models will not hold. However, even though the theoretical model may be too simple to capture all facets of real-life departure time choices, we have confidence that it captures some of the main effects, and it may still serve as a useful approximation. An obvious source of misspecification would be that the simple linear form of the marginal utilities is unrealistic for departure times far from t_0. It may however prove hard to remedy this, if one desires to retain a tractable functional form yielding closed form expressions of the expected utility function.[3]

Even if the theoretical scheduling model is correct, the assumption of optimal departure time choice which is necessary for the equivalence between scheduling and reduced form models, may be unrealistic in the context of SP data. However, the reduced form model may still be a good approximation of real-life behaviour where travellers can adjust their departure time on their daily commute until they reach an optimal solution. As such, we would have expected it to also be an acceptable approximation when applied to SP choices, at least for experienced travellers who consider the effect of their departure time choice, and may have developed some intuition or rule of thumb regarding the best departure time choice for their daily commute. The magnitude of the discrepancy between our scheduling and reduced form models, however, seems to reject this.

Finally, even if the scheduling and the reduced form models are indeed equivalent, the estimated scheduling preference parameters are likely to depend somewhat on how we

[3] Hjorth *et al.* (forthcoming), e.g., run into severe identification problems when attempting to estimate scheduling models with exponential marginal utility rates, which is one of the few continuous forms of marginal utility rates yielding closed form expressions of the expected utility function.

derive t_0. Wrong assumptions would cause a misspecification that causes the results of our scheduling model to be unreliable. This issue has so far been investigated very little. We test different ways to derive t_0 from the data to examine if this affects the discrepancy between scheduling and reduced form models. Results from our analysis indicate that, though the implied value of reliability, to some extent, depends on the derivation of t_0, this does not explain the discrepancy between the two models.

The rest of the paper is organized as follows. The next section presents the theoretical framework underlying our analysis. Section 3 describes the survey carried out and the resulting data used in the analysis. In section 4 we derive the empirical models used to estimate preferences, and in section 5 we discuss results and empirical findings. Section 6 concludes.

2 Theoretical framework

This section summarises the main assumptions and results in the scheduling model, which forms the basis of our analysis. The model is essentially equal to that of Fosgerau & Engelson (2011), except that we explicitly model how preferences can be heterogeneous across travellers.

2.1 The scheduling model

Our setting is a traveller making a journey from home to work, facing a risky travel time, i.e. travel time is not known with certainty in advance. For an outcome T (realised travel time) of the distribution of travel times, the traveller's utility is

$$\mathbf{U} = -c - \int_{d}^{t_0} H(t)dt - \int_{t_0}^{d+T} W(t)dt, \tag{1}$$

where d is departure time, c is the monetary cost of the trip, $H(t)$ is the marginal utility of being at home at time t instead of travelling, $W(t)$ is the marginal utility of being at work at time t rather than travelling, and t_0 is a time at which H and W intersecting.

Figure 1 illustrates t_0 and utility rates $H(t)$ and $W(t)$. We assume that H and W are continuous, and that H is non-increasing and $W(t)$ is non-decreasing. With these assumptions, t_0 can be interpreted as the point in time at which it becomes more attractive to be at work than at home provided that the commute trip can be made in no time.

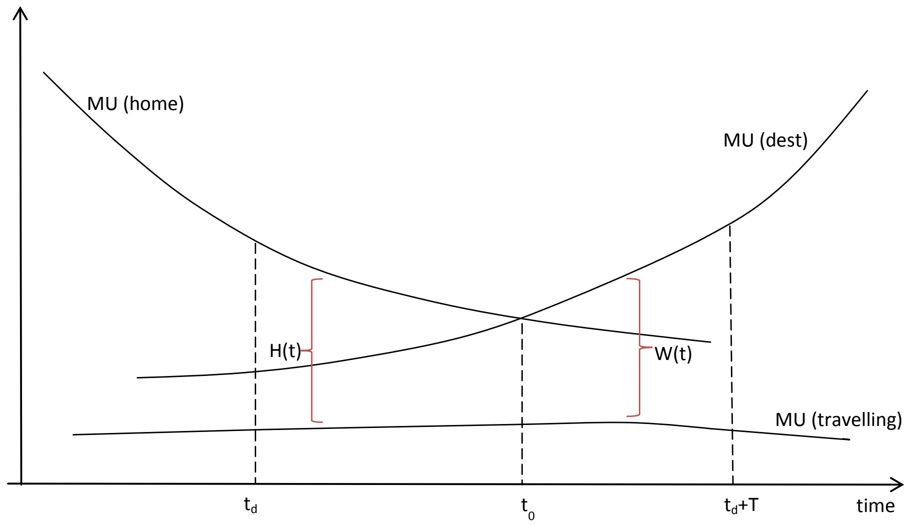


Figure 1: Illustration of scheduling preferences, t_0 and utility rates $H(t)$ and $W(t)$.

The point of intersection t_0 may vary over travellers, as different people are likely to have different time restrictions regarding obligations at home and at work. It is assumed that, for a given t_0, $H(t)$ and $W(t)$ are linear and depend only on the difference between time t and time t_0:

$$\begin{aligned} H(t) &= \gamma_0 + \beta_1(t - t_0), \\ W(t) &= \gamma_0 + \gamma_1(t - t_0). \end{aligned} \tag{2}$$

We assume that $\beta_1 \leq 0$ and $\gamma_1 \geq 0$ such that H is non-increasing and $W(t)$ is non-decreasing. This formulation implies that the additional marginal utility from being at work at time t' compared to time t_0 is independent of clock time as such - it depends only on $t' - t_0$. Similarly for the marginal utility of being at home.

When there is travel time variability, travel time T is a random variable. We assume the traveller knows the distribution of travel times and, based this distribution, can compute the expected utility associated with different departure times. Substituting (2) in (1) and manipulating, the expected utility becomes

$$E(\mathbf{U}) = -\Big(c + \frac{\gamma_1 - \beta_1}{2}(d - t_0)^2 + (\gamma_0 + \gamma_1(d - t_0))\mu_T + \frac{\gamma_1}{2}E(T^2)\Big). \tag{3}$$

where μ_T is the mean of the travel time distribution. We refer to this model as Model 1. In our analysis, we are also interested in the special case where $H(t)$ is constant, i.e. $\beta_1 = 0$. We refer to this special case as Model 2. This model is particularly interesting as it allows a simpler expression for the value of time.

2.2 The reduced form model

In this section, we present the reduced forms of Models 1 and 2 and the values of travel time and reliability they imply. The reduced form models are obtained from the full scheduling model by further assuming that the traveller chooses departure time optimally (i.e. to maximise expected utility). Differentiating (3) with respect to d and setting it equal to zero yields the optimal departure time:

$$d^* = t_0 - \frac{\gamma_1}{\gamma_1 - \beta_1}\mu_T \tag{4}$$

Inserting (4) into (3), and noting that $E\left(T^2\right) = \sigma_T^2 + \mu_T^2$ where σ_T^2 is the variance of the travel time distribution, we see that the optimal expected utility in Model 1, given the cost c and the travel time distribution, is

$$E(\mathbf{U}^*) = -\Big(c + \gamma_0\mu_T - \frac{\beta_1\gamma_1}{2(\gamma_1 - \beta_1)}\mu_T^2 + \frac{\gamma_1}{2}\sigma_T^2\Big). \tag{5}$$

The optimal expected utility depends on the mean and variance of the travel time distribution. Hence, in this model, the value of travel time (VTT) and the value of travel time variability (VTTV) are given by:

$$VTT = \frac{\partial E(\mathbf{U}^*)/\partial\mu_T}{\partial E(\mathbf{U}^*)/\partial c} = \gamma_0 - \frac{\beta_1\gamma_1}{(\gamma_1 - \beta_1)}\mu_T, \tag{6}$$

$$VTTV = \frac{\partial E(\mathbf{U}^*)/\partial\sigma_T^2}{\partial E(\mathbf{U}^*)/\partial c} = \frac{\gamma_1}{2}. \tag{7}$$

The reduced form of Model 2 is similar, except $\beta_1 = 0$, i.e. the optimal expected utility is

$$E(\mathbf{U}^*) = -\Big(c + \gamma_0\mu_T + \frac{\gamma_1}{2}\sigma_T^2\Big), \tag{8}$$

and the values of travel time and variability are:

$$VTT = \gamma_0, \tag{9}$$

$$VTTV = \frac{\gamma_1}{2}. \tag{10}$$

Interestingly, the values of travel time and reliability inferred from this model do not depend on the characteristics of the distribution of travel time.

3 Data and survey design

3.1 The stated preference survey

The data we use are from a Danish stated preference (SP) survey regarding TTV and the choice of departure time. The survey was carried out using an Internet questionnaire in the spring of 2014. The recruitment of respondents was handled by a market research agency, Epinion, using their existing Internet panel.

Rather than being representative of the population, the aim of the survey was to aid the development of an appropriate scheduling model to use in the valuation of TTV. It was therefore targeted at morning commute trips for car drivers. This is to achieve a relatively homogeneous sample of travellers and trips in terms of scheduling preferences, to exclude non-traders, and to avoid complicated issues related to scheduled public transport services. We aimed to sample approximately 1000 individuals.

We used stratified sampling to sample two roughly equally sized subsamples: Subsample 1 consisting of travellers who are used to commuting to work in congested conditions, and subsample 2 consisting of travellers who are used to commuting to work in uncongested conditions. The purpose of sampling equally from these two groups is to make sure we observe sufficient respondents who are used to congestion on their daily commute – which is rare in many parts of the country. We note that this stratified sampling likely causes the overall sample to be biased compared to the population of car commuters, and that this has to be handled somehow if data are used to estimate a representative national value of TTV. However, for research purposes, we believe our sampling strategy to be useful, because it provides a large subsample of people who are actually used to congestion and therefore possibly may have a different understanding and experience with the type of choices presented in the stated preference exercises.

The survey uses customised Internet questionnaires, containing a series of questions related to the traveller's most recent morning trip to work (the reference trip), e.g.:

- Travel time experienced on this day,
- Number of stops along the way, their duration, and whether these stops involved restrictions on time of day,
- Restrictions regarding departure time from home or arrival time at work,
- How often such a trip was made within the last month and the range of experienced

travel times,

- What the traveller considers to be his 'normal' travel time and departure time,
- What the traveller considers to be his free flow travel time (without queues or congestion), and his preferred departure time in the hypothetical situation where there were never queues or congestion,
- The cost of the trip (the respondent was instructed to focus on the variable costs only and the questionnaire computed the cost based on the stated trip distance and car fuel type, using default average values for fuel prices and depreciation/maintenance costs, but allowing respondents to alter these default values if they disagreed).

The survey contains two SP games, each consisting of 6 binary choices. The first game involves trade-offs between travel time, TTV and monetary travel cost, while the second also includes departure time. Figures 5 and 6 in the Appendix show examples of choice screens from each game. An overall aim in the survey was to keep the SP trade-offs as simple as possible, and hence TTV is described using travel time distributions that can attain only two values, a low value with probability $(1 - p)$ and a high value with probability p. The probability of an outcome is phrased as 'x out of 10 times, travel time is ... minutes', to avoid direct mentioning of the concept of probabilities. We deliberately avoid the phrasing of travel times as 'normal travel time' and 'delay', to minimize effects of potential reference-dependence and loss aversion (Kahneman & Tversky, 1979).

The levels of travel time, cost and departure time attributes are defined by pivoting around reference values, which are the experienced travel time, computed cost, and departure time of the reference trip. In order to ensure meaningful variation in the attributes, the survey was targeted at travellers whose reference trip lasted at least 10 minutes and cost at least 6 DKK.[4]

In all choices, one of the two departure time attributes is equal to the reference value, while the other is either smaller (earlier) or larger (later), and the number of earlier and later departures is balanced in the design. Departure time attributes are presented as clock times, rounded to the nearest 5 minutes to ease comparisons.

The cost attributes follow a similar pattern: One if the two cost attributes is equal to the reference cost, while the other is either smaller (gain) or larger (loss), and the number of gains and losses is balanced in the design. Costs were presented in DKK, rounded to

[4] 1 Euro (€) $\approx$ 7.5 DKK is used throughout.

the nearest integer. The smallest cost attribute value allowed is 5 DKK (values lower than this are truncated) and the smallest cost difference (between two alternatives) allowed is 1 DKK, to ensure values and comparisons are meaningful.

Each choice has four distinct travel time attributes (a low and a high for each alternative) – one of these is equal to the reference value and the remaining three are computed based on fixed ratios between the travel time attributes, which are taken from a list with six predefined levels. Again, these levels are balanced in the design, as is the position of the reference value. This ensures a very wide range of travel times in our analysis, as the same respondent may experience choices where all time attributes are greater than or equal to his reference travel time, as well as choices where all time attributes are smaller than or equal to his reference travel time. In each alternative, the probability p can take the values $0.1, 0.2, 0.4, 0.6, 0.8, 0.9$, to allow for as much variation as possible in the relation between mean travel time and variance (note that much of this variation is achieved through variations in the difference between the low and high travel time attribute).

For the sake of the statistical analysis, we have deliberately sought to ensure a wide range of attribute levels, rather than limiting analysis to 'realistic' ones. The ratio between the smallest and the largest of the four time attributes can be up to 2, such that the maximum travel time attribute can be as large as twice the size of the reference travel time, while the minimum travel time attribute can be as small as half the size of the reference travel time. The departure time attribute varies in both directions by up to 1.5 times the reference travel time, and the cost attribute by up to 500 DKK times the sum of the absolute deviations of the means and standard deviations of the two alternatives.

In both SP games, we used an orthogonal and partly randomised design rather than an 'optimised design'. This is due to robustness considerations since the optimised design requires the true scheduling model to be known in advance. The effects of assuming a wrong 'true' model are not sufficiently clear.

Finally, the questionnaire contained questions about the socio-economic background of the respondents as well as questions related to their transportation habits/possibilities, such as number of cars in the household, the nature of the parking facilities at their workplace, and whether they own a bicycle or possess a public transport travel card.

3.2 Sample statistics and description

A total of 1335 respondents participated in the survey. To obtain a balanced sample and ensure that the reference trip was salient in memory when respondents answer survey questions, we omitted from our analysis 116 individuals who did not answer all 12 SP choices or had an interview duration of more than 24 hours. It was possible to leave the survey Internet page temporarily and come back later to complete it, and we registered when respondents began the survey and when they last touched it. We do not require that respondents completed the survey (by answering all questions and clicking 'submit'), as the last questions concern income and the respondents' home and work addresses, which some may not want to answer.

Even though the survey targeted morning commute trips, a few students and pensioners with part-time jobs also answered the questionnaire. This was not intended, and since they were quite few (80 individuals), we chose to discard these interviews and focus on respondents whose primary occupation was as a wage earner or self-employed.

The remaining sample consists of 1139 respondents, each with 12 SP choices. For robustness reasons, we decided to also omit the following respondents in the analysis:

- Nine respondents who reported that they made three or more stops between home and work on their reference journey. We suspect that these people may interpret TTV differently than people with few or no stops, because a large part of the variation in travel time could be interpreted as due to the many stops along the way, and respondents with many stops may think they have the possibility to avoid some of the variability simply by rescheduling to move some of their errands to another (less congested) time of day.
- 80 individuals with reference travel time above 100 minutes or reference cost above 200 DKK: Due to the SP design, these respondents will experience rather large time and cost attribute values, and despite there are only a few respondents with such extreme values, they might have a substantial effect on the results, particular in the reduced form models where the travel time variance can become very large and cause numerical problems in the likelihood optimisation algorithm.

Eventually, estimation is based on 1050 respondents representing 78.65% of the total survey participants. Individuals who are used to congestion represent 45.7% of the

Table 1: Share of respondents by categorical variables and sub-sample

	Subsample S1 (used to congestion)	Subsample S2 (not used to congestion)
Share of the total sample population		
Male respondents	0.50	0.47
Respondents with a partner	0.91	0.91
Respondents with constraint at destination	0.55	0.57
Children < 10 years in the household	0.26	0.25
Respondents with constraint at origin	0.22	0.15
Respondents with less than high school education	0.02	0.02
High school or vocational school graduates	0.08	0.08
Those who completed higher education	0.51	0.44
Respondents with fixed working hours, same everyday	0.28	0.25
Respondents with fixed working hours, which can vary from day to day	0.15	0.17
Respondents with flexible working time with some fixed hours	0.35	0.34
Respondents with fully flexible working hours	0.18	0.18
Respondents with no stops on the commute	0.82	0.80
Respondents with 1 stops on the commute	0.15	0.17
Respondents with 2 stops on the commute	0.03	0.03

estimation sample. Table 1 and Table 2 present descriptive statistics of attributes and background variables for the estimation sample. The two sub-samples are largely similar in terms of various observed characteristics. However, the sub-samples are, to some extent, dissimilar on the basis of achievement in higher education, whether there are constraints regarding how early one can depart, annual respondent and household income and commute length and costs.

Table 2: Sample statistics for continuous variables by subsample

	Subsample S1 (used to congestion)			Subsample S2 (not used to congestion)		
	1st quart.	Mean	3rd quart.	1st quart.	Mean	3rd quart.
Reference travel time (min)	24.8	37.1	45.0	15.0	27.2	35.0
Normal travel time (min)	25	37	45	15	27.97	35
Reference travel cost (€)	1.97	4.7	6.3	1.9	4.08	4.9
Reference departure time‡	420	447.8	475	425	450.8	465
Normal departure time‡	420	443.5	470	420	447.9	465
Working hours per week	37	37.7	40	37	37.1	40
Weekly commute days	5	4.6	5	5	4.6	5
Household size	2	2.7	4	2	2.6	3
Respondent age (years)	41	49.4	58	41	50.5	59
Annual household income†	46.7	86.8	73.5	44.8	61.1	66.7
Annual respondent income†	73.3	132.9	128	66.7	100.9	120

‡ Departure times are in minutes since midnight

† Income is in €1000; mean values could be unreliable as no data cleaning is made for this variable.

4 Empirical framework

We carry out two separate analyses using the scheduling and reduced form models. Parameters of the scheduling models are estimated on data from choices where departure times are given as attributes and hence are not optimally chosen, while the same parameters under the reduced form models are estimated on data from choices where departure times are not given as attributes – instead they are assumed to be chosen optimally by travellers. We note that under this assumption of optimal departure times, the two approaches should in theory yield the same result.

To estimate the parameters in the scheduling and reduced form models we use logit models with the expected utilities in (3), (5) or (8) as 'choice utility'. In an initial modelling stage, we compared logit models with additive error terms to logit models with multiplicative error terms (Fosgerau & Bierlaire, 2009). Models with multiplicative errors yield much better fit. As a result, all subsequent models are estimated with multiplicative error terms. Estimation is carried out in Biogeme (Bierlaire, 2003, 2009).

Since Börjesson *et al.* (2012) used additive error terms, they formulate the discrete choice model in terms of differences in expected utility compared to a given reference. The way we introduce error terms means that it matters to our analysis how we normalise utility functions in our discrete choice model. In contrast to Börjesson *et al.* (2012), we formulate the discrete choice model in terms of a total expected cost measured in monetary units.

4.1 Estimation using the full scheduling model

To estimate preference parameters in the full scheduling model, we use a logit model with the expected utility in (3) as 'choice utility', allowing for different parameters in the two subsamples. With a multiplicative-errors specification, the choice utility of alternative j with attributes d_j, c_j and T_j, for a respondent in subsample S_k is

$$U_j = -\log\left[c_j + \frac{\gamma_1^{S_k} - \beta_1^{S_k}}{2}(d_j - t_0)^2 + (\gamma_0^{S_k} + \gamma_1^{S_k}(d_j - t_0))ET_j + \frac{\gamma_1^{S_k}}{2}ET_j^2\right] + \frac{\epsilon_j}{\mu^{S_k}}, \quad (11)$$

where the random errors ϵ_j are iid Gumbel distributed with scale parameter 1, and μ^{S_k} are error scale parameters to be estimated. In this and all other models, we normalized the cost coefficient to one so that the values of travel time and reliability are estimated in willingness-to-pay space (Train & Weeks, 2005).

Note that (11) depends on t_0, which has to be inferred or approximated from the data. There are many different options regarding how to infer t_0. One option is to use information about travel time T_{ff} and departure time d_{ff} under free flow (uncongested) travel conditions. We assume that free flow departure time is chosen optimally given the model in (3) and given a fixed travel time of T_{ff} (no travel time variability). This implies that (with separate coefficients for the two subsamples):

$$t_0 = d_{ff} + \frac{\gamma_1^{S_k}}{\gamma_1^{S_k} - \beta_1^{S_k}} T_{ff} \tag{12}$$

For future reference, we label this model SM1 (scheduling model 1). We also estimate the parameters in the special case, where $\beta_1^{S_k} = 0$, for both subsamples:

$$U_j = -\log\left[c_j + \frac{\gamma_1^{S_k}}{2}(d_j - t_0)^2 + (\gamma_0^{S_k} + \gamma_1^{S_k}(d_j - t_0))ET_j + \frac{\gamma_1^{S_k}}{2}ET_j^2\right] + \frac{\epsilon_j}{\mu^{S_k}} \tag{13}$$

We label this SM2 (scheduling model 2).

The definition of t_0 in (12) may be a rather strict assumption. In the discussion of our results (Section 5) we argue that it is interesting to relax the assumption in (12) and see if this affects the comparison of scheduling and reduced form models. To do so, we follow Tseng & Verhoef (2008) and define t_0 as a weighted average of departure time (d_{ff}) and preferred arrival time (PAT) under free flow(uncongested) travel conditions:

$$t_0 = \omega^{S_k} d_{ff} + (1 - \omega^{S_k})\text{PAT}, \tag{14}$$

where $\omega^{S_k} \in (0, 1)$ are sample-specific weights. We choose ω^{S_k} by estimating the scheduling models SM1 and SM2 with (12) replaced by (14) for a range of different values of the weights and choosing the values yielding the highest log-likelihood value. We label the resulting models SM1' and SM2'.

4.2 Estimation using reduced form models

To estimate preference parameters from the reduced form models, we use a discrete choice model with either (5) or (8) as choice utility. As mentioned above, we consider two versions of the reduced form model: One corresponding to (5), where β_1 is a free parameter, and another corresponding to (8), where β_1 is fixed to zero. We refer to these as RFM1 and RFM2 (reduced form model 1 and 2), respectively.

With multiplicative errors, the RFM1 becomes:

$$U_j = -\log\left[c_j + \theta_0^{S_k}\, E(T_j) + \theta_1^{S_k}\, (E(T_j))^2 + \theta_2^{S_k}\, \sigma_j^2\right] + \frac{\epsilon_j}{\mu^{S_k}} \tag{15}$$

Again, the random errors ϵ_j are iid Gumbel distributed with scale parameter 1, and μ^{S_k} are error scale parameters to be estimated. Now, if the scheduling model is true *and* respondents truly consider the optimal departure times for the given travel time distributions when choosing between alternatives (an underlying premise of the reduced form model) *and* respondents reveal the same preferences in both choice games, we would expect the following correspondences:

$$\theta_0^{S_k} = \gamma_0^{S_k} \tag{16}$$

$$\theta_1^{S_k} = -\frac{\beta_1^{S_k}\gamma_1^{S_k}}{2(\gamma_1^{S_k} - \beta_1^{S_k})} \tag{17}$$

$$\theta_2^{S_k} = \frac{\gamma_1^{S_k}}{2} \tag{18}$$

The RFM2 is the special case where $\beta_1^{S_k} = 0$, i.e. $\theta_1 = 0$ for both S_k:

$$U_j = -\log\left[c_j + \theta_0^{S_k}\, E(T_j) + \theta_2^{S_k}\, \sigma_j^2\right] + \frac{\epsilon_j}{\mu^{S_k}} \tag{19}$$

5 Results and discussion

5.1 Results from SM1, SM2, RFM1 and RFM2

Parameter estimates from the scheduling models in (11) and (13) are presented in Table 3 while estimates from the reduced form models (15) and (19) are shown in Table 4 . All parameters have the expected sign and are significant, except $\gamma_1^{S_1}$ in SM1 and both θ_0's in RFM1, which are positive, but not significantly different from zero. Both models reveal considerable differences between the two subsamples: People who are used to congestion have higher γ_0 and θ_0 and lower γ_1 and θ_2 (hence lower value of reliability) than people who are not used to congestion.

Based on both the SM1 and RFM1 models, we tested if there is structural difference in preferences based on experience to congestion. We did this by estimating a restricted model based on a pooled sample and separate models for each sub-sample, which together represent the unrestricted model. Based on the likelihood ratio test, the hypothesis

Table 3: Estimates from SM1 and SM2 with robust standard errors and z-values.

	SM1			SM2		
Parameter	Estimate	Std Err	z-value	Estimate	Std Err	z-value
Subsample S1 (used to congestion)						
$\beta_1^{S_1}$	-0.006	0.002	-2.85***			
$\gamma_0^{S_1}$	1.746	0.157	11.12***	1.737	0.142	12.251***
$\gamma_1^{S_1}$	0.002	0.002	1.00	0.007	0.001	4.558***
μ^{S_1}	3.233	0.264	12.23***	3.200	0.257	12.434***
Subsample S2 (not used to congestion)						
$\beta_1^{S_2}$	-0.008	0.002	-3.70***			
$\gamma_0^{S_2}$	1.225	0.115	10.67***	1.270	0.110	11.563***
$\gamma_1^{S_2}$	0.005	0.002	2.92***	0.011	0.002	5.566***
μ^2	2.871	0.237	12.10***	2.873	0.232	12.364***
Number of est. param.	8			6		
Number of obs.	6300			6300		
Log Likelihood value	-4018.43			-4027.9		

*** denotes significance at the 1% level, ** at the 5% level and * at the 10% level.

that preferences are similar between the two sub-samples is rejected (p-value 2% for the scheduling models and lower for the reduced form model). Consequently, in what follows, we present results separately for the two subsamples.

Based on log-likelihood tests, we conclude that the reduction from SM1 to SM2 (i.e. the test that β_1 is zero) is strongly rejected (p-value around 0.01%). A similar test for the reduction from RFM1 to RFM2 is also strongly rejected (p-value much smaller). Note that the assumption embodied in SM2 and RFM2 implies constant marginal utility for staying at the origin, instead of travelling, regardless of the time of day. Our results provide evidence against this, which is in line with previous research by Tseng & Verhoef (2008).

Table 5 shows the values of travel time and reliability computed based on the estimated parameters. Examining the difference between the two subsamples shows that, on average, individuals that are used to congestion (S1) have higher VTT and lower VTTV than respondents who are not used to congestion (S2). This result is consistent across models. The observed difference in the valuation of TTV (travel time) between the two subsamples can also be driven by self-selection or observable differences in characteristics. Since exposure to congestion is not random, those with strong preference against congestion may choose to work and reside in areas wherein they would minimize exposure to travel time variability. Moreover, though the two subsamples are largely comparable in terms of observed characteristics (see Table 2), differences in income and other covariates may also explain the observed dissimilarity in the valuation of TTV and travel time. However, since this is outside the scope of the paper, we refrain from further discussion on the issue and instead continue to describe the observed pattern.

Table 4: Parameter estimates of RFM1 and RFM2 with robust standard errors and z-values.

	RFM1			RFM2		
Parameter	Estimate	Std Err	z-value	Estimate	Std Err	z-value
Subsample S1 (used to congestion)						
$\theta_0^{S_1}$	0.095	0.276	0.343	2.083	0.136	15.29***
$\theta_1^{S_1} \cdot 10$	0.275	0.048	5.767***			
$\theta_2^{S_1} \cdot 10$	0.472	0.128	3.680***	0.412	0.110	3.76***
μ^{S_1}	2.963	0.313	9.461***	4.222	0.289	14.62***
Subsample S2 (not used to congestion)						
$\theta_0^{S_2}$	0.034	0.166	0.205	1.338	0.109	12.31***
$\theta_1^{S_2} \cdot 10$	0.247	0.036	6.834***			
$\theta_2^{S_2} \cdot 10$	0.842	0.154	5.462***	0.805	0.143	5.64***
μ^{S_2}	2.662	0.242	10.988***	3.344	0.264	12.69***
Number of est. param.	8			6		
Number of obs.	6300			6300		
Log Likelihood value	-3973.27			-4031.77		

*** denotes significance at the 1% level, ** at the 5% level and * at the 10% level.

Another important discrepancy is the large difference in VTTV between the scheduling models and the reduced form models. The magnitude of the difference is huge and similar to that found by Börjesson *et al.* (2012). While they cannot rule out that the discrepancy is caused by estimating the scheduling models on data without TTV, our results confirm that a discrepancy exists even when both types of models are estimated on data with uncertain travel times.

We can think of at least four possible explanations for the discrepancy. First, it may be that respondents do not behave similarly in the two choice games. It is possible, e.g., that the inclusion of the departure time attribute moves the focus of the respondents from TTV to departure times. This would be a problem if the change of focus causes respondents to neglect TTV in a degree that does not correspond to their real-life preferences. This is the 'focus bias explanation' suggested by Börjesson *et al.* (2012). It is a classic example of the drawbacks of using SP data, and it is of course not possible to check this explanation using SP data alone.

Table 5: Estimated values of travel time and TTV

	Subsample S1 (used to congestion)		Subsample S2 (not used to congestion)	
	SM1	RFM1	SM1	RFM1
Value of travel time variability	0.0001	0.0063	0.0003	0.0112
Value of travel time				
E(T)=10	0.23	0.09	0.17	0.07
E(T)=20	0.24	0.16	0.17	0.14
E(T)=30	0.24	0.23	0.18	0.20
E(T)=60	0.24	0.45	0.19	0.40
E(T)=90	0.25	0.67	0.20	0.60
	SM2	RFM2	SM2	RFM2
Value of travel time variability	0.0005	0.0055	0.0007	0.0107
Value of travel time	0.23	0.28	0.17	0.18

Value of travel time variability in €/min^2; and value of travel time in €/min

A second line of explanation concerns the appropriateness of the theory in section 2. Clearly, if the underlying assumptions in the scheduling model are incorrect, then the derived equivalence between scheduling models and reduced form models does not hold. However, even though the theoretical model is probably too simple to capture all facets of real-life departure time choices, we have confidence that it captures some of the main effects, and it may still serve as a useful approximation. An obvious source of misspecification would be that the simple linear forms of the marginal utility functions H and W is unrealistic for departure times far from t_0. Misspecification also arises if individuals had considered rescheduling possibilities, as this contradicts the assumption of exogenous scheduling preferences in the model. Another potential misspecification, also mentioned by Börjesson *et al.* (2012), is that the scheduling model does not allow for a disutility of uncertainty per se: The only thing that matters is when the respondent departs and arrives, so uncertainty enters solely through the expectation of the utility of arriving at a specific time. In reality, it may be that TTV affects the individual's perception of the travel time or the travel situation as such, and thus affects the measured preferences in other ways than through the expectation of the utility of arriving at a specific time. If this effect is captured by θ_2 in RFM1 and RFM2, but not to a similar degree by γ_1 in SM1 and SM2, it would cause a discrepancy between the model types consistent with what we find.

Even if the theoretical scheduling model is correct, the assumption of optimal departure time choice which is necessary for the equivalence between scheduling and reduced form models, may be unrealistic in the context of SP data. Exact equivalence demands that respondents, for each alternative in the choice set, visualise what would be the best departure time given the travel time distribution and what would be the consequences of this optimal departure time in terms of the different possible arrival times. This is almost certainly unrealistic! However, the reduced form model may still be a good approximation of real-life behaviour where travellers can adjust their departure time on their daily commute until they reach an optimal solution. As such, we might have expected it to also be an acceptable approximation in the analysis of SP choices, at least for experienced travellers who are used to considering the effect of their departure time choice, and may have developed some intuition or rule of thumb regarding the best departure time choice for their daily commute. The magnitude of the discrepancy between our scheduling and reduced form models however seems to reject this.

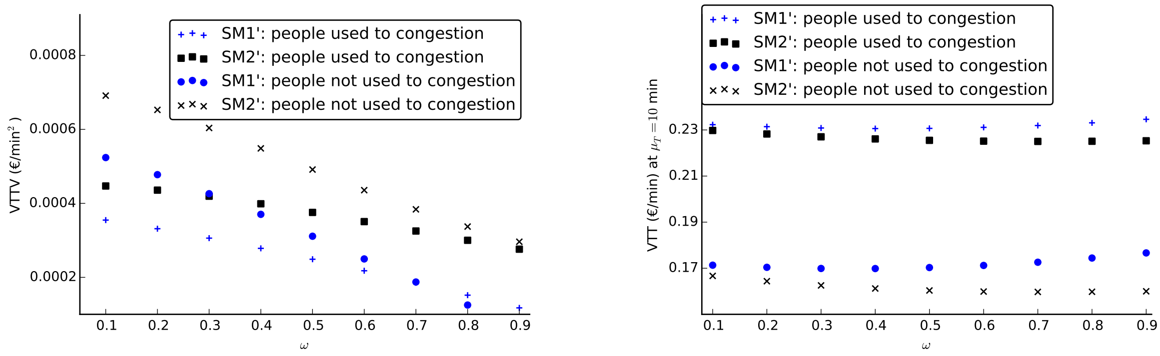
Finally, even if scheduling and reduced form models are indeed equivalent, the estimated preferences in SM1 and SM2 are likely to depend somewhat on how we derive t_0. If the assumptions in (12) are far from reality, this causes an empirical misspecification that renders the results of our scheduling models unreliable. This issue has so far been investigated very little. In order to compare the scheduling and reduced form models one can argue that our derivation of t_0 in (12) is at least consistent between the two model types, as it rests on an assumption of optimal departure time choice, which is the same assumption that yields the reduced form models. However, we think it is relevant (and fairly easy) to relax the strict assumptions in (12) and check how this affects our results. We do this in the next section.

5.2 Results from SM1' and SM2'

We estimated models SM1' and SM2' as described in Section 4. Various weights (ω) that locate t_0 at different points between d_{ff} and PAT were probed, and the implied values of mean travel time and TTV are shown in Figure 2.[5] In both models, parameter estimates and the VTTV are, to some extent, sensitive to the location of t_0. In particular, the closer t_0 is to PAT the higher the implied VTTV. This is so as the VTTV is entirely determined by the slope of $W(t)$, which becomes flatter as t_0 gets closer to PAT. However, the value

[5]We probed weights (0.1,0.2,0.3,...,0.9) with all possible combinations for the two subsamples.

of travel time is largely unaffected by a change in the location of t_0.



(a) The value of reliability

(b) The value of travel time

Figure 2: The values of travel time and TTV by location of t_0

For the full scheduling model, SM1', we found $\omega^{S_1} = 0.6$ (for people used to congestion) and with $\omega^{S_2} = 0.4$ (for those that are not used to congestion) yield the best model fit, in terms of the log-likelihood value. For the case where $\beta_1 \equiv 0$, the SM2' model, $\omega^{S_1} = 0.9$ and $\omega^{S_2} = 0.1$ provided the best model fit. The parameter estimates for these models are shown in Table 6. The implied value of mean travel time under SM1' (SM2') is similar to that under SM1 (SM2); however, the values of TTV inferred from these models exhibit certain dissimilarities.

In general however the values of travel time and TTV derived under the scheduling model, regardless of how the location of t_0 is determined, are considerably lower than the corresponding value from the reduced form model. Hence, the way in which the location of t_0 is determined does not seem to explain the observed discrepancy in the values of travel time and TTV between the scheduling and reduced form models. Moreover, SM1' is preferred to SM2' based on the Bayesian information criterion. Therefore, the choice between SM1/SM1' and SM2/SM2' is not linked to how t_0 is determined.

5.3 The value of standard deviation and reliability ratio

Thus far, the value of travel time variability measures the monetary value for a unit improvement in travel time variance. However, the unit of variance is not easy to interpret and this hinders comparison of the values of travel time variability between the current paper against those in most previous research. We therefore compute another measure of

Table 6: Estimates from SM1' and SM2', for best fitting values of ω

	SM1'			SM2'		
	Estimate	Std Err	z-value	Estimate	Std Err	z-value
Subsample S1 (used to congestion)						
$\beta_1^{S_1}$	-0.005	0.001	-3.71***			
$\gamma_0^{S_1}$	1.714	0.148	11.59***	1.690	0.141	11.99***
$\gamma_1^{S_1}$	0.003	0.001	2.59**	0.004	0.001	4.20***
μ^{S_1}	3.212	0.265	12.14***	3.147	0.248	12.69***
ω^{S_1}	0.6				0.9	
Subsample S2 (not used to congestion)						
$\beta_1^{S_2}$	-0.007	0.002	-4.53***			
$\gamma_0^{S_2}$	1.243	0.116	10.74***	1.250	0.110	11.40***
$\gamma_1^{S_2}$	0.006	0.002	3.39***	0.010	0.002	5.45***
μ^{S_2}	2.895	0.238	12.15***	2.851	0.232	12.31***
ω^{S_2}	0.4				0.1	
Number of est. param.		8			6	
Number of obs.		6300			6300	
Log Likelihood value		-4017.691			-4037.513	

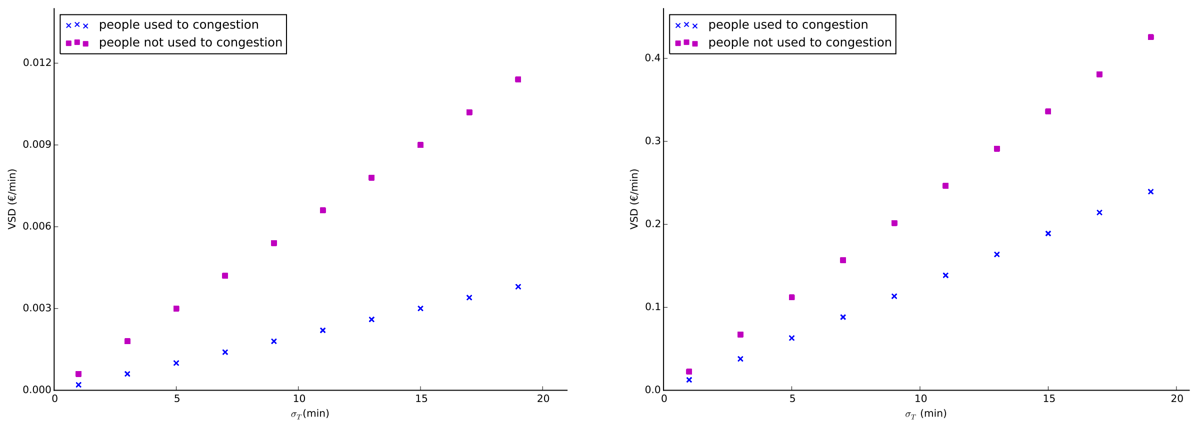
*** denotes signficance at the 1%, ** at the 5% level and * at the 10% level

the value of travel time variability:

$$\text{VSD} = \frac{\partial EU^{S_k}}{\partial \sigma_T} = \begin{cases} \gamma_1^{S_k}\sigma_T \text{ for SM1} \\ 2\theta_2^{S_k}\sigma_T \text{ for RFM1,} \end{cases} \tag{20}$$

to facilitate interpretation. This measure of travel time variability can be dubbed the value of standard deviation (VSD), and it represents the monetary value of reducing the standard deviation of travel time by one minute. As a result, the value of TTV is expressed in the same unit as the value of travel time. Hence, one can examine the relative importance of these quantities by taking the ratio of the marginal value of a minute's standard deviation and the marginal value of a minute's travel time. This quantity is known as the reliability ratio (RR).

Figure 3 portrays the VSD computed based on estimates from the full scheduling model (SM1 in table 3) and its reduced form model (RFM1 in table 4) for a range of values of the standard deviation of travel times (σ_T). Examining the VSD under the two models shows that, for a given σ_T, the value implied by the reduced form model is more than an order of magnitude larger. In contrast, for a given μ_T, the value of time implied by one of these models is less than 4 times the value suggested by the other. In both models, however, the value of standard deviation increases with σ_T. Moreover, the difference between the two subsamples in terms of the values of standard deviation is also apparent.



(a) SM1: Scheduling model 1

(b) RFM1: Reduced form model 1

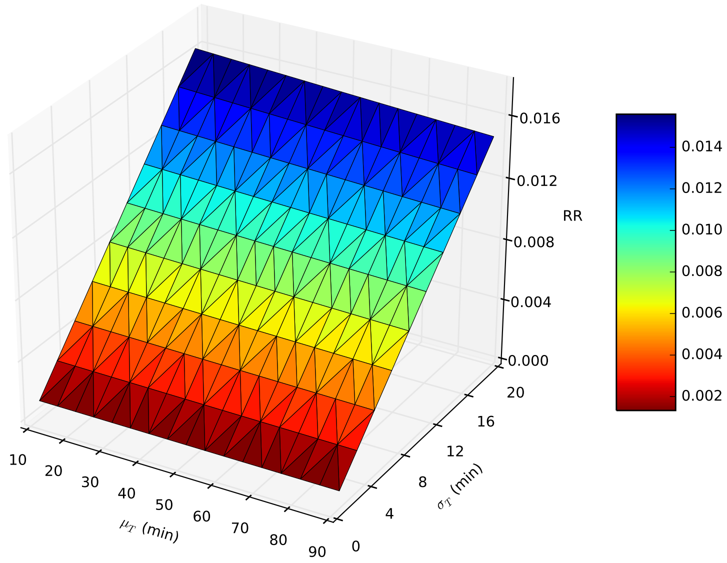
Figure 3: The values of standard deviation of travel time under SM1 and RFM1

We also computed the reliability ratio for different combinations of mean and standard deviation of travel time based on estimates from the full scheduling model (SM1) and its reduced form model (RFM1). The result of our computation for a subsample of individuals who are used to congestion is shown in Figure 4. For a given combination of (μ_T, σ_T), the reliability ratio implied by the reduced form model is more than an order of magnitude greater than the corresponding value suggested by the scheduling model. This disparity is largely produced by the difference in the value of reliability implied by the two models.

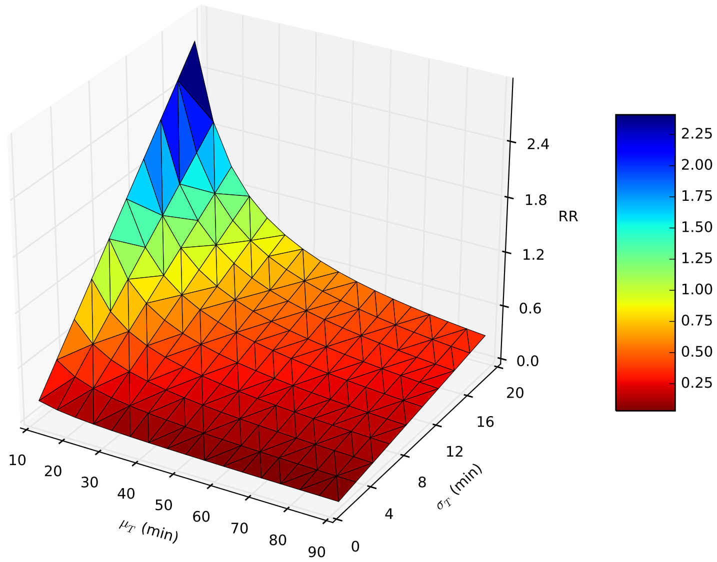
For a range of values of mean and standard deviation of travel time within the sample, the reliability ratio implied by the scheduling model is less than values reported in literature (see Carrion & Levinson (2012) and Kouwenhoven *et al.* (2014) for a recent review). However, the reliability ratio implied by the reduced form model is, for most combinations of the mean and standard deviation of travel time, comparable to values reported in the literature.

In the scheduling model, since the value of travel time depends only marginally on the level of μ_T (see Table 5), the reliability ratio barely varies in the dimension of μ_T. In the reduced form model, however, the reliability ratio varies in both dimensions as the values of travel time and VSD under this model depend, to a greater extent, on the level of mean and standard deviation of travel time.

While the scheduling model is preferred on theoretical grounds, applied to our data, it however produced a value of reliability that is not within a range of values one might expect. In contrast, the implied value of reliability under the reduced form model is, by



(a) SM1: Scheduling model 1



(b) RFM: Reduced form model 1

Figure 4: Reliability ratio by model for people used to congestion

and large, within a range of values reported in previous quantitative research. In this context, the reduced form model seemed to produce reasonable values of reliability while the scheduling model suggest values that are not in line with our expectation.

6 Conclusions

Using data from a stated preference survey, we compare the slope model of the scheduling approach and the implied reduced form model for measuring the value of travel time variability. Our work is one of few applications of the slope model to investigate the attitudes of car drivers towards travel time variability. Compared to previous studies (e.g. Börjesson *et al.*, 2012), we tested the implication of some model assumptions and used data better suited for comparing the two models.

The finding of the paper is that, despite the better data foundation, we are not able to empirically support the theoretical equivalence between these models. We find largely comparable average value-of-time estimates between the two models, which are consistent with values from other studies. However, the implied valuation of travel time variability for these models are very different. This finding, which is robust to alternative specification of the 'ideal arrival' time, is in line with the recent Swedish study by Börjesson *et al.* (2012). However, due to data better suited for comparing the two models we are in a position to rule out some of the potential explanations that were lined up for the observed discrepancy between the scheduling and reduced form models.

We provide the following potential explanations as to why the two models are different: First, it is possible that respondents in the stated choice experiment do not behave according to the theory. Since the model does not address rescheduling possibilities, it will be misspecified if respondents engage in rescheduling rather than acting according to the given schedule. It is also possible that the assumed linearity of the marginal utility function is causing a misspecification. Second, the complexity of the choice task may influence respondents to take decisions in ways that deviate from utility maximization. Rather than considering all attributes, respondents may have neglected some attributes or focused on a subset of these to simplify their decision-making. The small parameter estimate for travel time variability under the scheduling model could be linked to this phenomenon. This is a focus bias explanation as discussed by Börjesson *et al.* (2012). Moreover, under the scheduling model, scheduling considerations alone may not sufficiently capture the valuation of travel time variability. There could be disutility associated with the uncertainty per se, which is not accounted for in the model.

The similarity of the results in Börjesson *et al.* (2012) and our results suggest that there may well be a more fundamental problem of estimating the valuation of travel time variability based on data from hypothetical experiments. Brownstone & Small (2005) were able to estimate the value of travel time variability based on data from real behaviour. It is therefore recommended that before we can rule out potential hypothetical bias, models should be estimated based on data from real behaviour.

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Appendix

Table 7: List of notations

Notation	Description
d, d^*	Departure time, optimal departure time
T	Travel time
c	Monetary cost of a trip
$\mathbf{U}, \mathbf{U}^*$	Scheduling utility, optimal scheduling utility
$H(\cdot), W(\cdot)$	Marginal utility rates at origin and destination
β_0, β_1	Intercept and slope of utility rate at origin
γ_0, γ_1	Intercept and slope of utility rate at work
μ_T, σ_T^2	Mean and variance of travel time
E	Expected value operator
T_{ff}	Travel time under free flow (uncongested) condition
d_{ff}, PAT	Departure time and preferred arrival time under free flow
$\theta_0, \theta_1, \theta_2$	Preference parameters under the reduced form models
t_0	Desired arrival time when travel time is zero
ω	A number in $(0, 1)$ such that $t_0 = \omega d_{ff} + (1 - \omega)$PAT
ϵ	Gumbel distributed random error term
μ	Error scale parameter
iid	independent and identically distributed

Choice situation 1 out of 12

Which journey do you prefer?

You choose your own departure time. Your preferred departure time may differ between A and B.

	Journey A	Journey B
Travel time	9 out of 10 times the journey takes **11** minutes 1 out of 10 times the journey takes **20** minutes	8 out of 10 times the journey takes **10** minutes 2 out of 10 times the journey takes **16** minutes
Cost	20 DKK	21 DKK
Your choice?	O	O

Figure 5: Example of choice screen (translated from Danish)– choice without departure time attribute

Choice situation 7 out of 12

Which journey do you prefer?

Each journey has a fixed departure time.

	Journey A	Journey B
Departure time	8:00 AM	7:40 AM
Travel time	6 out of 10 times the journey takes **17** minutes 4 out of 10 times the journey takes **25** minutes	2 out of 10 times the journey takes **12** minutes 8 out of 10 times the journey takes **20** minutes
Cost	21 DKK	39 DKK
Your choice?	O	O

Figure 6: Example of choice screen (translated from Danish) – choice with departure time attribute

CHAPTER 2

Valuation of travel time variability with endogenous scheduling of a meeting*

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Abstract

This paper examines the choice of an optimal meeting time in a situation where individuals can freely choose meeting times. It extends the model of Fosgerau, Engelson and Franklin (*Journal of Urban Economics*) to incorporate the notion of an agreed meeting time and a penalty that may be imposed when one arrives later than the meeting time. The model considers two individuals who choose departure and meeting times in the presence of uncertain travel times for a trip towards a joint meeting. The paper shows the existence of a unique optimal meeting time and a unique Nash equilibrium in departure times. It finds that an increase in the variance of the difference between individual travel times is costly for both individuals. It also finds that an increase in travel time variance of one person is costly to both. Compared to Fosgerau, Engelson and Franklin, the introduction of a lateness penalty allows an additional mechanism through which a change in travel time variance of one individual affects the pay-off of both individuals.

Keywords: travel time variability; value of reliability; endogenous scheduling of a meeting; scheduling preferences

JEL code: R41

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1 Introduction

The valuation of travel time variability (TTV) has received increasing attention over the past few decades, both from researchers and policy makers. Starting from earlier workers, inter alia by Small (1982) and Noland & Small (1995), there is a growing body of research measuring the cost of TTV. Empirical evidence also shows that the economic costs associated with TTV are significant (see Li *et al.* , 2010; Carrion & Levinson, 2012, for recent review). As a result, the valuation of TTV is increasingly being recognised as an important component in economic appraisal of transport projects.

The scheduling model (e.g. Vickrey, 1969; Small, 1982; Fosgerau & Karlstrom, 2010) is the standard theoretical framework for measuring the cost of TTV. This model associates the aversion to TTV with the cost of arriving earlier or later than desired. It considers travellers who, facing a fixed arrival time and TTV, choose departure times to maximise expected utility, from which the cost of TTV is derived. However, the assumption of exogenously determined arrival time lacks generality which, even in situations such as a meeting where arrival times may not be pre-determined, excludes the possibility that the desired arrival time could depend on the distribution of travel times. Moreover, the framework takes scheduling choices merely as an individual matter. In contrast, scheduling choices can be widely seen as optimal reactions in contexts involving social interaction (Basu & Weibull, 2003; Fosgerau & Small, 2010). In many cases, such as a meeting, activities performed at the other end of a trip involve more than one person. In such circumstances, one's choices and travel outcomes can also affect all others involved.

Recently, Fosgerau *et al.* (2014) addressed these issues by building a model wherein scheduling preferences are interdependent. The model considers two individuals who, facing a random travel time towards a joint in-person meeting, choose departure times to maximise scheduling utility. It is assumed that individuals prefer to depart later and arrive earlier. The authors showed the existence of unique equilibrium departure times and derived the value of a marginal reduction in the scale of TTV. In particular, they found that an increase in the variance of the difference in individual travel times is costly to both individuals, an insight overlooked by the customary scheduling model.

In the Fosgerau *et al.* (2014) model, the strategic interaction is induced by the property that a meeting starts only when both individuals have arrived at the destination. The model assumes that players choose an optimal time to start the meeting. In the current paper, we explicitly examine the choice of an optimal meeting time and the implication of allowing for this choice on the value of TTV. We achieved this by extending their model to include the notion of an agreed time to start the meeting and a penalty that may be imposed when one arrives later that this time. The penalty represents an emotional cost (embarrassment) of arriving later than the designated meeting time. The extension introduces an additional mechanism through which TTV can affect equilibrium scheduling utility.

We examine the optimal meeting time as an agreement outcome in the course of bargaining. As we consider homogeneous individuals, the bargaining solution coincides with the choice of individually optimal meeting time. We show the existence and uniqueness of equilibrium departure times and an optimal meeting time. We also find that, at equilibrium, an increase in the variance of the difference in travel times is costly to both individuals. Moreover, an increase in the variance of individual travel times is found to be costly to both individuals. While our results about the cost of TTV are qualitatively similar to those in Fosgerau *et al.* (2014), in their model, the effect of increased variance in individual travel times occurs fully through the variance of the travel time difference. Our model also allows the variance of individual travel times to have a direct effect on equilibrium utility.

The paper is organised as follows. Section 2 describes the game theoretic framework, Section 3 and Section 4 analyse choice equilibrium departure times and optimal meeting time. We provide a numerical example in Section 5. On the basis of optimality conditions, Section 6 examines the cost of TTV while the last section concludes.

2 The model

Our model builds upon the framework by Fosgerau *et al.* (2014), who considered scheduling choices of two individuals who take a trip of random duration towards a joint in-person meeting. Suppose the meeting is started only when both individuals have arrived at the meeting place. Assuming options other than departure time are separable and are optimally chosen, the choice under each individual's control is departure time. Given other things, departure times determine the possibility of arriving early or late; and the aversion to these outcomes induces preferences over departure times.

Preferences can be represented by a utility function. Suppose utility is derived at a time dependent rate (e.g. see Vickrey, 1973; Tseng & Verhoef, 2008; Fosgerau & Engelson, 2011). Let h be the utility rate at the origin before the trip and $\gamma > 0$ be the utility rate at destination from the joint meeting. Since starting the meeting requires the presence of both individuals and, given travel duration, time of arrival is determined by a chosen departure time, either individual's choice influences the outcome to both thereby inducing strategic interaction in decision making.

Suppose the marginal utility of time at destination before the meeting and the marginal utility of time spent travelling are equal and normalized to zero. Thus, h and γ are expressed relative to the marginal utility of travel time. It is also assumed through out that h is non-negative, continuously differentiable and strictly decreasing, i.e., $h' < 0$.

In this setting, Fosgerau *et al.* (2014) denoted the scheduling utility to an individual i who departs at time d_i and arrives at destination at time $a_i = d_i + T_i$ as

$$U_i\left(d_i, d_j\right) = \int_0^{d_i} h_i(x)\,\mathrm{d}x - \gamma_i \max(a_i, a_j) \tag{1}$$

where $T_i \geq 0$ is random travel time and $\max(a_i, a_j)$ is the time at which the meeting starts. The time at which each person begins the activity at the origin as well as the time when the meeting ends is normalized to zero without loss of generality.

We extended this formulation by introducing the notion of an agreed meeting time m and a penalty that may be imposed when a person arrives later than this time. The penalty represents an emotional cost, embarrassment, of arriving later than the appointed meeting time. Letting $\eta > 0$ denote the marginal lateness penalty and assuming that individuals are homogeneous, hence $\gamma_i = \gamma_j = \gamma$, we arrive at the following utility function

$$U_i(d_i, d_j, m) = \int_0^{d_i} h(x)\,\mathrm{d}x - \gamma\left[\frac{a_i + a_j}{2} + \frac{|d_i - d_j - \Delta|}{2}\right] - \eta \max(a_i - m, 0), \tag{2}$$

where $\max(a_i - m, 0)$ is the duration of lateness when player i arrives later than m, $\Delta \equiv T_j - T_i$ and $\max(a_i, a_j) = \frac{a_i + a_j}{2} + \frac{|d_i - d_j - \Delta|}{2}$. We assume that Δ has a compact support and a continuous cumulative distribution function Φ_Δ.

The decision making process is both strategic and sequential as depicted in Figure 1. Once individuals agreed to meet, they will set a time for their meeting. Then each individual chooses an optimal departure time considering the agreed meeting time and the departure time choice of the other person. The strategic interaction at this stage is induced by the physical property that a meeting starts at the time when both individuals arrive at the destination. Finally, actual outcomes are known when travel times are realized. The choice of a meeting time influences the choice of a departure time; and the latter choice is made conditioning on the chosen meeting time.

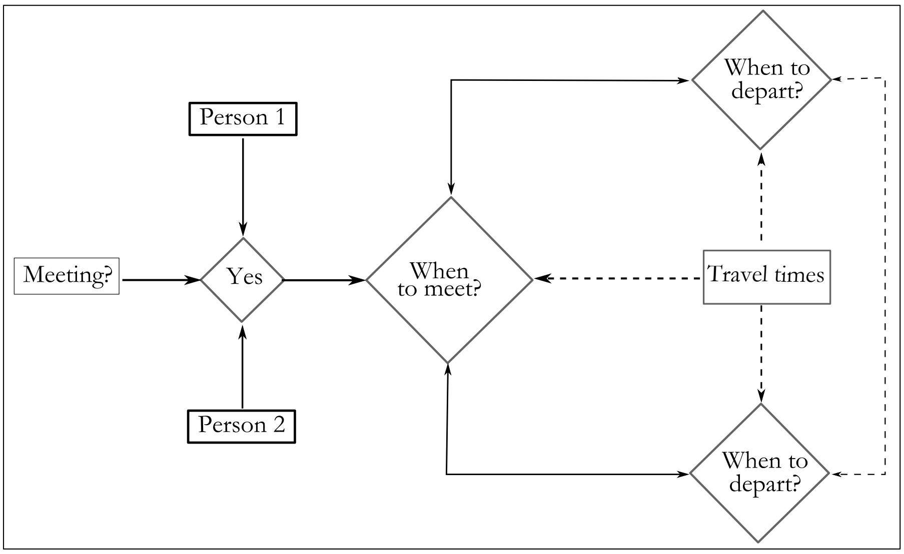

Figure 1: Hierarchy of travel decision making

Travel times are not known with certainty before the trip. But we assume individuals know the distribution of travel times and take this in to account when they make scheduling choices. It is also assumed that each individual i chooses departure and meeting times in a continuous fashion from a compact interval D_i and M, respectively, each of which are wide enough to encompass all relevant possibilities. We also assumed that an individual's choice of departure and meeting times does not influence the distribution of travel times. Moreover, individual travel times, T_i, are assumed to have identical continuous cumulative distribution function F_{T_i} that has a compact support and mean μ_i.

3 Equilibrium departure times

Suppose agreement is reached to start the meeting at a particular time, m. Given m and player j's choice of departure time, each player i chooses his departure time to maximize expected utility. Formally, optimal departure times can be expressed in terms of a best response correspondence. Individual i's best response correspondence $r_i(.)$ is the set of optimal departure times for any given choice of departure time by the other person:

$$r_i(d_j) = \{d_i^* \in D_i : u_i\left(d_i^*; d_j, m\right) \geq u_i\left(d_i; d_j, m\right), \text{ for all } d_i \in D_i\}$$

where $u_i = E[U_i]$ and E is the expected value operator. Each best response satisfies

$$\begin{aligned} \frac{\partial u_1}{\partial d_1} &= h\left(d_1\right) - \gamma \Phi_\Delta\left(d_1 - d_2\right) - \eta\left[1 - F_{T_1}\left(m - d_1\right)\right] = 0 \\ \frac{\partial u_2}{\partial d_2} &= h\left(d_2\right) + \gamma \Phi_\Delta\left(d_1 - d_2\right) - \eta\left[1 - F_{T_2}\left(m - d_2\right)\right] = \gamma \end{aligned} \tag{3}$$

The derivation of (3) is shown in Appendix B. The condition implies that an individual's optimal departure time equates the marginal utility of time at destination before departure and the marginal expected utility loss from delaying departure.

Since the pay-off to an individual player depends on the choice of both individuals, an independent choice of departure time may not maximize individual utility. Nash equilibrium is obtained when players choose departure times such that their choices are mutually best responses to one another. The existence of this equilibrium is established based on properties of best response mappings stated in the following lemma. The proof of this lamma along with all other proofs is given in Appendix C.

Lemma 1 *Each $r_i(d_j)$ is a continuous function.*

At Nash equililibrium, no individual has an incentive to unilaterally deviate from the equilibrium profile. This is the case if each best response satisfies $0 \leq h\left(d_i\right) \leq \gamma + \eta$ since otherwise deviation from equilibrium is gainful. A pair of feasible departure times $\left(d_i^*, d_j^*\right)$ identifies a Nash equilibrium profile if for every individual i, $u_i\left(d_i^*, d_j^*\right) \geq u_i\left(d_i, d_j^*\right)$ for every $d_i \in D_i$. An equilibrium profile can be defined as a fixed point of players' best response functions: $r(d) = r_i(d_j) \times r_j(d_i)$. At equilibrium, a departure time profile is chosen such that (3) holds simultaneously for both individuals. Adding (3) across individuals and rearranging yields the joint requirement for Nash equilibrium:

$$\sum_{i=1}^{2}\Big[h(d_i)-\eta\left(1-F_{T_i}\left(m-d_i\right)\right)\Big]=\gamma \tag{4}$$

The requirement in (4) will be satisfied if the following condition holds:

Condition 1 $\lim_{x\to\infty}\Big[h(x)\Big]<\eta+\frac{\gamma}{2}$

Condition 1 guarantees general existence of Nash equilibrium and is maintained throughout the paper. Unless this condition holds there will be an incentive to deviate from the equilibrium profile.

Theorem 1 *There is a unique Nash equilibrium in departure times.*

While each person's optimal departure time depends on the probability with which one person arrives later than the other, $\Phi\left(.\right)$, the equilibrium profile (4) does not depend on this term. The fact that $r_i'\left(d_j\right)>0$ (see the proof of Theorem 1) indicates that departure times are strategic complements suggesting that the choice of departure time by one person elicits a similar response from the other. So that the two effects cancel out at equilibrium. In other words, if person i departs late then j's incentives to depart early are very small as it will not help to start the meeting earlier.

We examined the equilibrium departure time profile conditional on a chosen meeting time, hence $d_i^*=d_i(m)$ for both i. The maximum expected utility at this stage is found by inserting the equilibrium profile (d_i^*,d_j^*) in (2), which yields

$$\begin{aligned}V_i(m)\equiv\int_0^{d_i(m)}h\left(x\right)\mathrm{d}x-\frac{\gamma}{2}\left[\textstyle\sum_i d_i\left(m\right)+\sum_i\mu_{T_i}+\displaystyle\int\left|d_i\left(m\right)-d_j\left(m\right)-x\right|\phi_\Delta\left(x\right)\mathrm{d}x\right]\\-\eta\int_{m-d_i(m)}^{+\infty}\Big(d_i\left(m\right)+x-m\Big)f_{T_i}\left(x\right)\mathrm{d}x\end{aligned} \tag{5}$$

A change in m affects utility through equilibrium departure times besides its direct effect on the penalty of lateness. $V_i\left(m\right)$ plays a an important role when examining the choice of optimal start time for the meeting.

4 Optimal meeting time

In the previous section, we assumed a chosen meeting time to examine equilibrium behaviour in departure times. The meeting is not determined as part of Nash equilibrium since, if either player is given control over it, he or she will take the other player's choice of departure time as given and choose to depart as late as possible. This, however, rules out the possibility that players could cooperate to set a meeting time that could make both of them better off. Such a meeting time can be obtained as an agreement outcome in a process of negotiation.

The negotiation could start with one of the players selecting an easily agreeable time. Players then try to find other agreeable points in M which are better for both. Eventually, both players are required to agree upon what would be a desirable time for the meeting.

When heterogeneous, players can have conflicting interests as to what would be a desirable meeting time. However, since players are homogeneous in our case, they have perfectly compatible interests. As a result, an optimal choice of meeting time for one player is also optimal for the other. We assume that the agreement outcome is Pareto optimal, i.e., there is no other feasible meeting time that can make a player better off without making the other player worse off. With Pareto optimal agreement outcomes, the homogeneity of players reduces the bargaining problem to an individual maximisation problem. The following condition ensures that the solution to the bargaining problem is unique.

Condition 2 *The density of travel times, $f_{T_i}(.)$, is non-increasing at the optimally allowed travel time, $T_i = (m^* - d_i^*)$, i.e., $f'_{T_i}(m^* - d^*) \leq 0$.*

Some distributions such as the exponential and uniform have this condition as a general feature while for others such as the normal distribution, the condition requires that the optimally allowed travel time should lie at a point where the density function is downward sloping. The following theorem states the existence and uniqueness of an optimal meeting time.

Theorem 2 *There exists an optimal meeting time m^* satisfying the condition*

$$\eta\Big[1 - F_{T_i}\Big(m^* - d_i(m^*)\Big)\Big] - \gamma\Big[1 - \Phi_\Delta\Big(d_i(m^*) - d_j(m^*)\Big)\Big]d'_j(m^*) = 0. \tag{6}$$

The optimal meeting time m^* is unique by Condition 2.

In what follows we derive the optimal meeting time and illustrate the nature of $V_i(.)$ with a numerical example.

5 Numerical example

This section illustrates the existence and uniqueness of an optimal meeting time using a numerical example. Let $h\left(d_i\right) = \left(1 - d_i\right)$ for $0 \leq d_i \leq 1$ so that $h'\left(d_i\right) = -1$; and assume individual travel times are independent and uniformly distributed, $T = T_i \sim U\left(0, 1\right)$, such that the travel time difference Δ has density

$$\phi_\Delta\left(x\right) = \begin{cases} x + 1 \text{ if } -1 < x < 0 \\ 1 - x \text{ if } 0 \leq x < 1, \end{cases}$$

which is a triangular distribution.

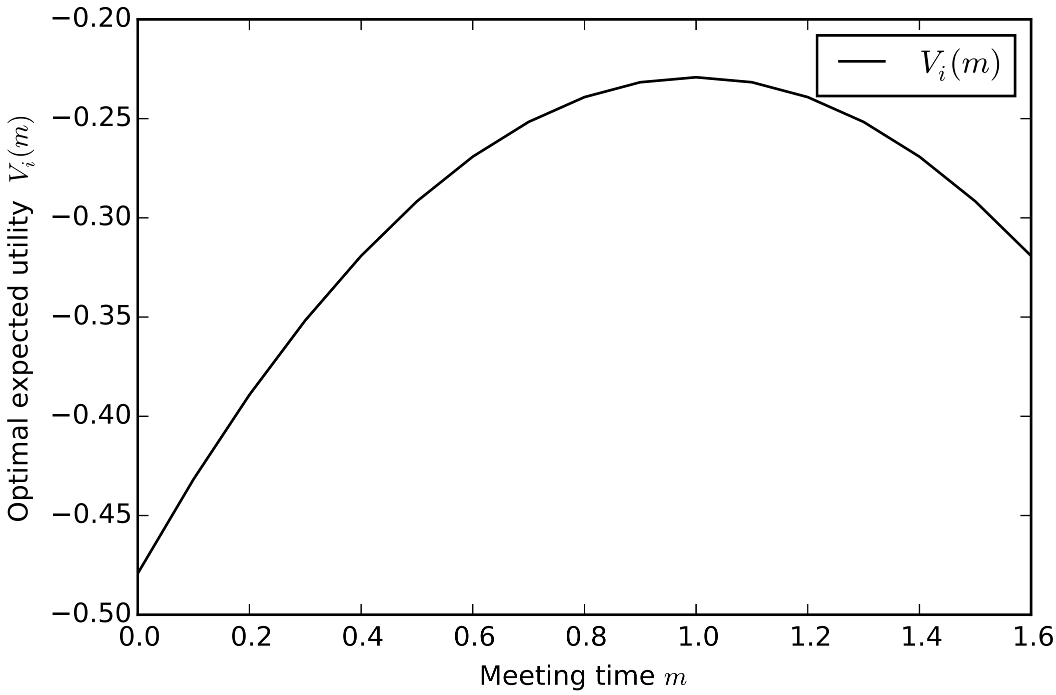

Figure 2: Optimal expected utility as a function of m

In this setting, the requirement for Nash equilibrium (4) becomes

$$2(1-d) - 2\eta(1 - F_T(m-d)) = \gamma,$$

where $d = d_i$ for both i is used noting the symmetry of equilibrium. Using $F_T(x) = x$ for $x \in [0, 1)$ and rearranging we obtain the equilibrium departure time $d^* = d(m)$ as

$$d(m) = \frac{2[1 + \eta(m-1)] - \gamma}{2(1+\eta)} \quad \text{for } m \in [d, d+1)$$

Therefore $d'(m) = \frac{\eta}{1+\eta} \in (0, 1)$. By inserting the relevant expression in (6), we obtain the optimal meeting time $m^* = 2 - \gamma$.

For the case where $\gamma = \eta = 1$, the optimal meeting time is $m^* = 1$ and the equilibrium departure times profile is $(0.25, 0.25)$. The optimal expected utility, $V_i(m)$, is concave on a feasible interval of meeting times (see Figure 2). Since the slope of $f_T(.)$ is zero, the condition for unique optimal meeting time is always satisfied. In fact, we have $V_i''(m) = -\frac{\eta}{1+\eta} < 0$ indicating uniqueness of the optimal meeting time.

6 The value of travel time variability

Each person's maximal expected utility is obtained by inserting the equilibrium departure time profile and optimal meeting time in to the expected utility function. From this maximal utility function, we then derive each person's valuation of a reduction in the variance of travel times and the variance of the travel time difference. This is achieved by considering the effect on equilibrium utility of a marginal reduction in σ_i or σ. To do this, we denote each T_i in a convenient form $T_i = \mu_i + \sigma_i X_i$ where μ_i and σ_i are its mean and standard deviation respectively; and X_i is a standardized random variable with zero mean, unit variance, continuous density f_{X_i} and a cumulative distribution F_{X_i} with a compact support. Likewise, we denote Δ in a similar form $\Delta = \mu + \sigma X$ where X is a standardised variable with zero mean and unit variance, a continuous density function ϕ_X and a continuous and increasing cumulative distribution Φ_X.

Since equilibrium choices are determined based on a given (σ, σ_i), a change in either of these parameters induces individuals to adjust their optimal choices. However, since choices are optimized in a continuous fashion, the change does not cause a second-order effect on utility through own choices (due to the envelope theorem). More precisely, for each individual i, the indirect effect of the change occurs only through person j's choice of departure time.

Theorem 3 *Starting from equilibrium, a small increase in the scale of travel time difference, σ, is costly to both individuals.*

The result in Theorem 3 is qualitatively similar to that in Fosgerau *et al.* (2014), which is expected since σ does not enter the added term in our model. However, although σ does not enter the cost of arriving later than the designated meeting time, the effect to each person i of a change in σ also occurs through a change in person j's departure time.

Theorem 4 *Suppose individual travel times, X_i, exhibit same degree of variability, i.e., $\sigma_i = \sigma_j$. Then, starting from equilibrium where individuals do not allow for TTV, i.e., $m^* - d_i^* = \mu_i$, a small increase in σ_i is costly to both individuals.*

An equilibrium where individuals do not allow for TTV, i.e., $m^* - d_i^* = \mu_i$, may not occur in the model, however, it is required to prove the assertion in Theorem 4.

Since the conventional scheduling model takes the case of a single traveller, a change in the variance of travel times for one person is independent of the pay-offs to the other player. Due to the strategic interaction in our model, however, such a change influences scheduling choices and hence the equilibrium utility to the other person.

While the result in Theorem 4 is qualitatively similar to Fosgerau *et al.* (2014), it differs in two respects. Firstly, in our model a change in the travel time variance of person i directly affects own equilibrium utility beyond and above its effect through the variance of the travel time difference. This is so since σ_i enters person i's equilibrium utility through the penalty of lateness. In contrast, in Fosgerau *et al.* (2014) the effect on utility of a change in the travel time variance of person i occurs fully through the variance of the travel time difference. Secondly, they find that the effect of an increase in the travel time variance of person i depends on how travel times are correlated. However, since we assume homogeneous players with $\sigma_i = \sigma_j$, an increase in σ_i makes random travel times less synchronized (increases the variance of travel time difference). Therefore, it is costly to both individuals.

7 Conclusion

In this paper, we extended a model by Fosgerau *et al.* (2014) examining a meeting between two individuals by introducing a notion of designated meeting time and a penalty that may be imposed when one arrives later than this time. In this model, we showed that there exists a unique equilibrium in departure times and a unique optimal meeting time. We found that an increase in the variance of the difference between individual travel times is costly for both individuals. It is also found that an increase in travel time variance of one person is costly to both individuals. Compared to Fosgerau *et al.* (2014), the introduction of a lateness penalty allows an additional mechanism through which a change in travel time variance of one individual affects the pay-off of both individuals.

Results in our paper crucially depend on the homogeneity of players. In a future work, the model can be extended to include non-homogeneous individuals. Moreover, our model considered a meeting involving only two individuals. This can also be extended to accommodate a situation involving more than two individuals.

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Appendix

A Notation

Table 1: List of notation

Notation	Description
i, j	Individuals, two
d_i	Individual i's departure time
T_i	Individual i's travel time
Δ	Travel time difference, $T_j - T_i$
X_i	Individual i's standardised travel time
X	Standardised travel time difference
a_i	Individual i's arrival time: $a_i = d_i + T_i$
m	Designated meeting time
r_i	Individual i's best response function
U_i	Individual i's utility function
u_i	Individual i's expected utility
V_i	u_i at equilibrium departure times
W_i	V_i at equilibrium departure times and optimal meeting time
γ	Marginal utility of time spent in a joint meeting
η	Marginal cost of arriving later than an agreed meeting time
h	Marginal utility of spending time at the origin
μ_i	Individual i's mean travel time
μ	Mean of the travel time difference
σ	Standard deviation of the travel time difference
σ_i	Standard deviation of travel time for individual i
d_i^*, m^*	Shows the the variable is at equilibrium or optimum
$f_{T_i}, f_{X_i}, \phi_\Delta, \phi_X$	Probability density function of the relevant variable
$F_{T_i}, F_{X_i}, \Phi_\Delta, \Phi_X$	Cumulative probability density of the relevant variable

B Derivation

Derivation of (3)**.** We obtain the first order conditions for Nash equilibrium in (3) by differentiating each person's expected utility with respect to own departure time, holding m and the other person's choice of departure time constant. That is, for each i and $j \neq i$, the optimal choice departure time for person i satisfies

$$\frac{\partial u_i}{\partial d_i} = \frac{\partial}{\partial d_i}\left[\int_0^{d_i} h\left(x\right)\mathrm{d}x - \frac{\gamma}{2}\left(d_i + d_j + \mu_i + \mu_j + \int \left|d_i - d_j - x\right| \phi_\Delta\left(x\right)\mathrm{d}x\right)\right.$$
$$\left. - \eta \int_{m-d_i}^{\infty} \left(d_i + x - m\right) f_{T_i}\left(x\right)\mathrm{d}x\right] = 0. \quad (7)$$

Noting that

$$\left|d_i - d_j - x\right| = \begin{cases} d_i - d_j - x & \text{for } x \leq d_i - d_j \\ -\left(d_i - d_j - x\right) & \text{for } x \geq d_i - d_j \end{cases}$$

and letting $\vartheta \equiv d_i - d_j$, we obtain[1]

$$\begin{aligned}\frac{\partial}{\partial d_i}\int \left|\vartheta - x\right| \phi_\Delta\left(x\right)\mathrm{d}x &= \frac{\partial}{\partial d_i}\left[\int_{-\infty}^{\vartheta}\left(\vartheta - x\right)\phi_\Delta\left(x\right)\mathrm{d}x - \int_{\vartheta}^{\infty}\left(\vartheta - x\right)\phi_\Delta\left(x\right)\mathrm{d}x\right] \\ &= \int_{-\infty}^{\vartheta}\phi_\Delta\left(x\right)\mathrm{d}x - \left(\int_{\vartheta}^{\infty}\phi_\Delta\left(x\right)\mathrm{d}x\right) \\ &= \int_{-\infty}^{\vartheta}\phi_\Delta\left(x\right)\mathrm{d}x - \left(1 - \int_{-\infty}^{\vartheta}\phi_\Delta\left(x\right)\mathrm{d}x\right) \\ &= 2\Phi_\Delta\left(\vartheta\right) - 1\end{aligned}$$

Moreover, we have

$$\frac{\partial}{\partial d_i}\int_{m-d_i}^{\infty}\left(d_i + x - m\right) f_{T_i}\left(x\right)\mathrm{d}x = \int_{m-d_i}^{\infty} f_{T_i}\left(x\right)\mathrm{d}x = 1 - F_{T_i}\left(m - d_i\right)$$

Substituting these expressions in (7), we obtain:

$$\frac{\partial u_i}{\partial d_i} = h(d_i) - \frac{\gamma}{2}\left(1 + 2\Phi_\Delta(\vartheta) - 1\right) - \eta\left(1 - F_{T_i}\left(m - d_i\right)\right) = 0$$

Therefore, the expression in (3) follows straightforwardly by rearranging this and replacing ϑ by $d_i - d_j$. ∎

[1] We differentiate under the integral applying:

$$\frac{\partial}{\partial x}\left(\int_{\ell(x)}^{b(x)} g(x,z)\,\mathrm{d}z\right) = b'(x)g\left(b(x),x\right) - \ell'(x)g\left(\ell(x),x\right) + \int_{\ell(x)}^{b(x)}\frac{\partial g(x,z)}{\partial x}\mathrm{d}z$$

C Proofs

Proof of Lemma 1. Since $u_i(.; d_j, m)$ is continuous and strictly concave and D_i is compact and convex, $r_i(.)$ is a single-valued correspondence, hence a function. Since each best response function can be defined as an intersection set of two convex sets

$$r_i(d_j) = D_i \cap \{d_i^* : u_i(d_i^*; d_j, m) = \max_{d_i \in D_i} u_i(d_i; d_j, m)\}$$

with the latter being the upper contour set of the concave function u_i, it follows that each best response is also convex-valued. Moreover, since the constraint correspondence for each person's maximisation problem is compact-valued and fixed, hence continuous, each $r_i(d_j)$ is upper hemi-continuous by Berge's maximum theorem. ■

Proof of Theorem 1. The proof has two parts - existence and uniqueness. We first provide the proof for existence based on a fixed point theorem.

Existence: Let $D \equiv D_i \times D_j$ and $d \equiv (d_i, d_j)$, and define a correspondence $r : D \rightrightarrows D$ by $r(d_i, d_j) = r_i(d_j) \times r_j(d_i)$. The requirement for Nash equilibrium amounts to the existence of a profile d^* such that $d^* \in r(d)$. This is essentially a fixed point of $r(d)$. Hence, a fixed point theorem can be used to show the existence of Nash equilibrium.

If D is convex and compact, and $r(.)$ is non-empty, upper hemi-continuous, and compact- and convex-valued, then $r(d)$ has a fixed point by Kakutani's fixed point theorem. D inherits the required properties as each D_i has these properties. Moreover, since each r_i is non-empty, upper hemi-continuous and compact- and convex-valued by Lemma 1, it follows that $r(.)$ is also non-empty, upper hemi-continuous, and compact- and convex-valued. Since $r(d)$ satisfies the requirements for Kakutani's fixed point theorem, it has at least one fixed point hence Nash equilibrium by definition.

Uniqueness: For an equilibrium profile d^*, when person i chooses d_i^* and j responds with $r_j(d_i^*)$, i has no incentive to unilaterally deviate from the equilibrium profile; hence $d_i^* = r_i(r_j(d_i^*))$. Each response function, $r_i(.)$, is continuous by Berge's maximum theorem. If $r_i'(d_j) < 1$ for $\forall d_j \in D_j$, at most one equilibrium can exist. The proof is suggested by Fosgerau *et al.* (2014), and is shown to hold as follows.

From (3) we have best response functions $r_i(d_j)$ satisfying:

$$0 = h\Big(r_i(d_j)\Big) - \gamma\Phi_\Delta\Big(r_i\,(d_j) - d_j\Big) - \eta\,[1 - F_{T_i}\,(m - r_i(d_j))]$$

Now differentiate and rearrange this expression to obtain

$$\frac{\partial r_i\,(d_j)}{\partial d_i} = \frac{-\gamma\phi_\Delta\Big(r_i\,(d_j) - d_j\Big)}{h'\Big(r_i\,(d_j)\Big) - \gamma\phi_\Delta\Big(r_i\,(d_j) - d_j\Big) - \eta f_{T_i}\Big(m - r_i\,(d_j)\Big)},$$

which is positive and strictly less than one since $h'(.) < 0$ and probability density functions are non-negative. Therefore, for both i and all $(d_i, d_j) \in D$, $\frac{\partial r_i(r_j(d_i))}{\partial d_i} = \frac{\partial r_i(d_j)}{\partial d_j}\frac{\partial r_j(d_i)}{\partial d_i} < 1$ ensuring the existence of at most one equilibrium profile. ■

Proof of Theorem 2. The existence of an optimal meeting time m^* follows since each $V_i(.)$ is continuous on a closed and bounded interval M such that there exists some $m^* \in M$ with $V_i(m^*) \geq V_i(m)$ for all $m \in M$. Applying the Envelope theorem, the requirement for an optimal meeting time can be given by

$$\frac{\mathrm{d}V_i(m)}{\mathrm{d}m} = \frac{\partial V_i(m)}{\partial d_j}\frac{\partial d_j(m)}{\partial m} + \frac{\partial V_i(m)}{\partial m} = 0 \tag{8}$$

where $\frac{\partial V_i(m)}{\partial d_i} = 0$ since $V_i(d_i^*; d_j, m) \geq V_i(d_i; d_j, m)$ for all $d_i \in D_i$. Moreover, we have

$$\frac{\partial V_i}{\partial m} = -\eta\frac{\partial}{\partial m}\int_{m-d_i(m)}^{\infty}\Big(d_i(m) + x - m\Big) f_{T_i}\,(x)\,\mathrm{d}x = \eta\Big(1 - F_{T_i}\,(m - d_i(m))\Big) \geq 0$$

and

$$\begin{aligned}\frac{\partial V_i}{\partial d_j} &= -\frac{\gamma}{2} - \frac{\gamma}{2}\frac{\partial}{\partial d_j}\left[\int_{-\infty}^{\vartheta}\Big(\vartheta - y\Big)\phi_\Delta\,(y)\,\mathrm{d}y - \int_{\vartheta}^{\infty}(\vartheta - y)\,\phi_\Delta\,(y)\,\mathrm{d}y\right] \\ &= -\gamma\Big[1 - \Phi_\Delta\,(\vartheta)\Big] \\ &= -\frac{\gamma}{2} < 0\end{aligned}$$

where $\vartheta \equiv d_i(m) - d_j(m)$. The last expression is obtained by symmetry of equilibrium which implies that $\vartheta = 0$. Then, we derive $\frac{\partial d_i}{\partial m}$ by differentiating the equilibrium condition:

$$0 = \frac{\partial}{\partial m}\Big[\sum\nolimits_i h\,(d_i(m)) - \gamma\Phi_\Delta\,(\vartheta) + \eta\sum\nolimits_i\Big(1 - F_{T_i}\,(m - d_i(m))\Big)\Big]. \tag{9}$$

Since the equilibrium is symmetric, *i.e.*, $d(m) = d_i(m)$ for both i, we will have $\Phi_\Delta(\vartheta) = \frac{1}{2}$.

Differentiating the resulting expression yields

$$h'\Big(d(m)\Big)d'(m) - \eta\Big(1 - f_T\left(m - d(m)\right)\Big) = 0, \tag{10}$$

which can be rearranged to obtain

$$d'(m) = \frac{-\eta f_T\left(m - d(m)\right)}{h'\left(d(m)\right) - \eta f_T\left(m - d(m)\right)} \tag{11}$$

Since $f_T(.) \geq 0$ and $h'(.) < 0$, we have $d'(m) \in (0,1)$. Therefore, the first order condition for an optimal meeting time will be

$$\eta\Big[1 - F_{T_i}\left(m - d_i(m)\right)\Big] - \gamma\Big[1 - \Phi_\Delta\left(\vartheta\right)\Big]d_2'\left(m\right) = 0, \tag{12}$$

as given in Theorem 2.

Uniqueness: If each $V_i''\left(m\right) < 0$, then the optimal meeting time is unique. To show whether this is the case, differentiate (9) while noting the symmetry of equilibrium (hence $d_i(m) = d(m)$, $F_{T_i}\left(x\right) = F_T\left(x\right)$ and $\Phi_\Delta\left(0\right) = \frac{1}{2}$) which yields

$$V''\left(m\right) = -\frac{\gamma}{2}d''\left(m\right) - \eta\left[1 - d'\left(m\right)\right]f_T\left(m - d\left(m\right)\right) \tag{13}$$

We want to show that (13) is less than zero at the point where $m = m^*$ and $d = d\left(m^*\right)$, which holds if

$$d''\left(m\right) = \frac{\partial}{\partial m}\left[-\frac{\eta f_T\left(m - d\left(m\right)\right)}{h'\left(d\left(m\right)\right) - \eta f_T\left(m - d\left(m\right)\right)}\right] \geq 0$$

Differentiating and rearranging, one can state the inequality as

$$f_T'\left(m - d\right) \leq \frac{h''\left(d\left(m\right)\right)d'\left(m\right)f_T\left(m - d\left(m\right)\right)}{\left(1 - d'\left(m\right)\right)h'\left(d\left(m\right)\right)} \leq 0,$$

which holds by Condition 2. ■

Proof of Theorem 3. Each person's maximal expected utility is obtained by inserting the optimal meeting time, m^*, in to $V_i(m)$:

$$W_i \equiv \int\limits_0^{d_i(m^*)} h(x)\,\mathrm{d}x - \frac{\gamma}{2}\left[\sum\nolimits_i \Big(d_i(m^*) + \mu_i\Big) + \int\left|d_i(m^*) - d_j(m^*) - \mu - \sigma x\right|\phi_X(x)\,\mathrm{d}x\right]$$
$$- \eta\int_{\tau_i}^{+\infty}\Big(d_i(m^*) + \mu_i + \sigma_i x - m^*\Big)f_{X_i}(x)\,\mathrm{d}x \tag{14}$$

where $\tau_i = \frac{m - d_i(m^*) - \mu_i}{\sigma_i}$. To each individual i, the effect on equilibrium expected utility,

W_i, of a marginal change in σ is

$$\frac{\mathrm{d}W_i}{\mathrm{d}\sigma} = \frac{\partial W_i}{\partial d_j}\frac{\partial d_j}{\partial \sigma} + \frac{\partial W_i}{\partial \sigma}$$

where

$$\begin{aligned}
\frac{\partial W_i}{\partial d_j} &= -\frac{\gamma}{2}\left[1 + \frac{\partial}{\partial d_j}\int |d_i - d_j - \mu - \sigma x|\, \phi_X(x)\,\mathrm{d}x\right] \\
&= -\frac{\gamma}{2}\left[1 + \frac{\partial}{\partial d_j}\left(\int\limits_{-\infty}^{\tau}(d_i - d_j - \mu - \sigma x)\,\phi_X(x)\,\mathrm{d}x - \int\limits_{\tau}^{\infty}(d_i - d_j - \mu - \sigma x)\,\phi_X(x)\,\mathrm{d}x\right)\right] \\
&= -\frac{\gamma}{2}\left[1 - \int_{-\infty}^{\tau}\phi_X(x)\,\mathrm{d}x + \int_{\tau}^{\infty}\phi_X(x)\,\mathrm{d}x\right] \\
&= -\gamma\left[\int_{\tau}^{\infty}\phi_X(x)\,\mathrm{d}x\right] \leq 0
\end{aligned}$$

where the inequality follows since $E(X) = 0$, and $\tau \equiv \frac{d_i - d_j - \mu}{\sigma}$ is used to conserve space. One can derive $\frac{\partial d_j}{\partial \sigma}$ by differentiating (3) and (4) as:

$$\begin{aligned}
h'(d_i)\frac{\partial d_i}{\partial \sigma} - \frac{\gamma}{\sigma}\phi_X(\tau)\left(\frac{\partial d_i}{\partial \sigma} - \frac{\partial d_j}{\partial \sigma} - \tau\right) - \frac{\eta}{\sigma_i}\frac{\partial d_i}{\partial \sigma}f_{X_i}(\tau_i) = 0 \\
h'(d_i)\frac{\partial d_i}{\partial \sigma} + h'(d_j)\frac{\partial d_j}{\partial \sigma} - \frac{\eta}{\sigma_i}\frac{\partial d_i}{\partial \sigma}f_{X_i}(\tau_i) - \frac{\eta}{\sigma_j}\frac{\partial d_j}{\partial \sigma}f_{X_j}(\tau_j) = 0
\end{aligned}$$

Denoting $c_i \equiv h'(d_i) - \frac{\eta}{\sigma_i}f_{X_i}(\tau_i) < 0$ and collecting like terms, we obtain

$$\frac{\partial d_i}{\partial \sigma} = -\frac{\frac{\gamma}{\sigma}\phi_X(\tau)\frac{\partial d_j}{\partial \sigma} + \frac{\gamma}{\sigma}\phi_X(\tau)\tau}{\left(c_i - \frac{\gamma}{\sigma}\phi_X(\tau)\right)} = -\frac{c_j}{c_i}\frac{\partial d_j}{\partial \sigma}$$

Solving the last two terms for $\frac{\partial d_j}{\partial \sigma}$ yields

$$\frac{\partial d_j}{\partial \sigma} = \frac{\gamma\phi_X(\tau)\,c_i}{\sigma c_i c_j - \gamma\phi_X(\tau)(c_i + c_j)}\tau \equiv \kappa\tau$$

where $-1 < \kappa \leq 0$. Also, noting that $E(X) = 0$,

$$\begin{aligned}
\frac{\partial W_i}{\partial \sigma} &= -\frac{\gamma}{2}\frac{\partial}{\partial \sigma}\left[\int_{-\infty}^{\tau}(d_i - d_j - \mu - \sigma x)\,\phi_X(x)\,\mathrm{d}x - \int_{\tau}^{+\infty}(d_i - d_j - \mu - \sigma x)\,\phi_X(x)\,\mathrm{d}x\right] \\
&= -\frac{\gamma}{2}\left[-\int_{-\infty}^{\tau}x\phi_X(x)\,\mathrm{d}x + \int_{\tau}^{+\infty}x\phi_X(x)\,\mathrm{d}x\right] \\
&= -\frac{\gamma}{2}\left[\int_{\tau}^{\infty}x\phi_X(x)\,\mathrm{d}x + \int_{\tau}^{+\infty}x\phi_X(x)\,\mathrm{d}x\right] \\
&= -\gamma\int_{\tau}^{\infty}x\phi_X(x)\,\mathrm{d}x \leq 0
\end{aligned}$$

The inequality follows since $E(X) = 0$. Therefore,

$$\begin{aligned}\frac{\mathrm{d}W_i}{\mathrm{d}\sigma} &= -\gamma \left[\int_\tau^\infty \phi_X(x)\,\mathrm{d}x\right]\kappa\tau - \gamma \int_\tau^\infty x\phi_X(x)\,\mathrm{d}x \\ &= -\gamma \left[\int_\tau^\infty (x+\kappa\tau)\,\phi_X(x)\,\mathrm{d}x\right] < 0\end{aligned}$$

since

$$\frac{\mathrm{d}W_i}{\mathrm{d}\sigma}\Big(x, \kappa = 0\Big) \leq \frac{\mathrm{d}W_i}{\mathrm{d}\sigma}\Big(x, \kappa\Big) \leq \frac{\mathrm{d}W_i}{\mathrm{d}\sigma}\Big(x, \kappa = -1\Big) < 0$$

Thus, an increase in the standard deviation of the difference in travel times is costly for both individuals. ■

Proof of Theorem 4. This proof has two parts. First, we show that a small increase in σ_i is costly to individual i, *i.e.*,

$$\frac{\mathrm{d}W_i}{\mathrm{d}\sigma_i} = \frac{\partial W_i}{\partial \sigma}\frac{\partial \sigma}{\partial \sigma_i} + \frac{\partial W_i}{\partial d_j}\frac{\partial d_j}{\partial \sigma_i} + \frac{\partial W_i}{\partial \sigma_i} \leq 0$$

where

$$\frac{\partial W_i}{\partial \sigma_i} = -\eta \frac{\partial}{\partial \sigma_i}\int_{\tau_i}^\infty (d_i + \mu_i + \sigma_i x - m)\, f_{X_i}(x)\,\mathrm{d}x = -\eta \int_{\tau_i}^\infty x f_{X_i}(x)\,\mathrm{d}x \leq 0$$

For simplicity we suppress the $*$ superscripts. The following notations are also used to economise space: $\lambda \equiv \gamma/\sigma$, $\eta_i \equiv \eta/\sigma_i$, $c_i \equiv h'(d_i) - \eta_i f_{X_i}(\tau_i) < 0$, $s_i \equiv c_i - \lambda\phi_X(\tau) < 0$ and $\varphi_i \equiv \eta_i f_{X_i}(\tau_i) \geq 0$.

The derivative $\frac{\partial d_j}{\partial \sigma_i}$ can be derived from (3) and (4). Differentiating the second expressions in (3), we have

$$\begin{aligned}0 &= h'(d_j)\frac{\partial d_j}{\partial \sigma_i} + \left(\frac{\partial d_i}{\partial \sigma_i} - \frac{\partial d_j}{\partial \sigma_i} - \frac{\partial \sigma}{\partial \sigma_j}\tau\right)\lambda\phi_X(\tau) - \eta_j f_{X_j}(\tau_j)\frac{\partial d_j}{\partial \sigma_i} \\ 0 &= s_j \frac{\partial d_j}{\partial \sigma_i} + \lambda\phi_X(\tau)\frac{\partial d_i}{\partial \sigma_i} - \lambda\phi_X(\tau)\,\tau\frac{\partial \sigma}{\partial \sigma_j}\end{aligned}$$

therefore

$$\frac{\partial d_i}{\partial \sigma_i} = \tau\frac{\partial \sigma}{\partial \sigma_j} - \frac{s_j}{\lambda\phi_X(\tau)}\frac{\partial d_j}{\partial \sigma_i} \tag{15}$$

Also, differentiating the joint equilibrium condition in (4),

$$h'(d_j)\frac{\partial d_j}{\partial \sigma_i} + h'(d_i)\frac{\partial d_i}{\partial \sigma_i} - \varphi_i\frac{\partial d_i}{\partial \sigma_i} - \eta_i f_{X_i}(\tau_i)\,\tau_i - \eta_j f_{X_j}(\tau_j)\frac{\partial d_j}{\partial \sigma_i} = 0$$

and rearranging it we obtain:

$$\frac{\partial d_i}{\partial \sigma_i} = \frac{\varphi_i \tau_i}{c_i} - \frac{c_j}{c_i} \frac{\partial d_j}{\partial \sigma_i} \tag{16}$$

Solving for $\frac{\partial d_j}{\partial \sigma_i}$ from (15) and (16) and rearranging we obtain

$$\frac{\partial d_j}{\partial \sigma_i} = \frac{\lambda \phi_X(\tau)}{\lambda \phi_X(\tau)(c_i c_j) - c_i c_j} \left[\varphi_i \tau_i - c_i \tau \frac{\partial \sigma}{\partial \sigma_j} \right]$$

Starting from an equilibrium point where $m - d_i = \mu_i$, then $\tau_i = 0$ implying that

$$\frac{\partial d_j}{\partial \sigma_i} = -\frac{\lambda \phi_X(\tau) c_i}{\lambda \phi_X(\tau)(c_i + c_j) - c_i c_j} \tau \frac{\partial \sigma}{\partial \sigma_j} \equiv -\omega \tau \frac{\partial \sigma}{\partial \sigma_j}$$

where $0 \leq \omega < 1$ since $c_i < 0$ and $\frac{\partial \sigma}{\partial \sigma_i} \geq 0$. Therefore,

$$\begin{aligned}
\frac{\mathrm{d}W_i}{\mathrm{d}\sigma_i} &= \frac{\partial W_i}{\partial \sigma} \frac{\partial \sigma}{\partial \sigma_i} + \frac{\partial W_i}{\partial d_j} \frac{\partial d_j}{\partial \sigma_i} + \frac{\partial W_i}{\partial \sigma_i} \\
&= \left[-\gamma \int_\tau^\infty x \phi_X(x)\, \mathrm{d}x \right] \frac{\partial \sigma}{\partial \sigma_i} + \gamma \left[\int_\tau^\infty \phi_X(x)\, \mathrm{d}x \right] \omega \tau \frac{\partial \sigma}{\partial \sigma_j} - \eta \int_{\tau_i}^\infty x f_{X_i}(x)\, \mathrm{d}x \\
&= -\gamma \int_\tau^\infty \left(\frac{\partial \sigma}{\partial \sigma_i} x - \omega \tau \frac{\partial \sigma}{\partial \sigma_j} \right) \phi_X(x)\, \mathrm{d}x - \eta \int_{\tau_i}^\infty x f_{X_i}(x)\, \mathrm{d}x \\
&= -\gamma \frac{\partial \sigma}{\partial \sigma_i} \int_\tau^\infty (x - \omega \tau) \phi_X(x)\, \mathrm{d}x - \eta \int_{\tau_i}^\infty x f_{X_i}(x)\, \mathrm{d}x
\end{aligned}$$

The last expressions follows as $\sigma_i = \sigma_j$ is assumed, which implies that

$$\frac{\partial \sigma}{\partial \sigma_j} = \frac{\partial \sigma}{\partial \sigma_i} = 2(\sigma_i - \rho \sigma_j) = 2(\sigma_i - \rho \sigma_i) = 2\sigma_i(1 - \rho) \leq 0$$

where the inequality follows since the correlation coefficient ρ lies in the interval $[-1, 1]$. Since $E(X_i) = 0$ and $E(X) = 0$, we have:

$$\frac{\mathrm{d}W_i}{\mathrm{d}\sigma_i}\Big(x, \omega = 0\Big) \leq \frac{\mathrm{d}W_i}{\mathrm{d}\sigma_i}\Big(x, \omega\Big) \leq \frac{\mathrm{d}W_i}{\mathrm{d}\sigma_i}\Big(x, \omega = 1\Big) < 0$$

therefore, an increase in σ_i is costly for individuals i.

Now we prove the second assertion in Theorem 4 that a small increase in σ_j is costly to individual i, *i.e.*,

$$\frac{\mathrm{d}W_i}{\mathrm{d}\sigma_j} = \frac{\partial W_i}{\partial \sigma} \frac{\partial \sigma}{\partial \sigma_j} + \frac{\partial W_i}{\partial d_j} \frac{\partial d_j}{\partial \sigma_j} \leq 0$$

We already derived component of this expression except, $\frac{\partial d_i}{\partial \sigma_i}$, which can derived from (15) and (16) as

$$\frac{\varphi_i \tau_i}{\lambda \phi_X(\tau)} - \tau \frac{\partial \sigma}{\partial \sigma_i} - \frac{s_i}{\lambda \phi_X(\tau)} \frac{\partial d_i}{\partial \sigma_i} = \frac{\varphi_i \tau_i}{c_j} - \frac{c_i}{c_j} \frac{\partial d_i}{\partial \sigma_i}$$

solving for $\frac{\partial d_i}{\partial \sigma_i}$ and rearranging we obtain

$$\frac{\partial d_i}{\partial \sigma_i} = \frac{\lambda \phi_X(\tau) - c_j}{\lambda \phi_X(\tau) c_i - s_i c_j} \varphi_i \tau_i + \frac{\lambda \phi_X(\tau) c_j}{\lambda \phi_X(\tau)(c_i + c_j) - c_i c_j} \tau \frac{\partial \sigma}{\partial \sigma_i}$$

hence for $\tau_i = 0$, the expression reduces to

$$\frac{\partial d_i}{\partial \sigma_i} = \frac{\lambda \phi_X(\tau) c_j}{\lambda \phi_X(\tau)(c_i + c_j) - c_i c_j} \tau \frac{\partial \sigma}{\partial \sigma_i} \equiv \zeta \tau \frac{\partial \sigma}{\partial \sigma_i}$$

where $0 \leq \zeta < 1$. Combining the relevant expressions, we have:

$$\begin{aligned}
\frac{\mathrm{d}W_i}{\mathrm{d}\sigma_j} &= \frac{\partial W_i}{\partial \sigma} \frac{\partial \sigma}{\partial \sigma_j} + \frac{\partial W_i}{\partial d_j} \frac{\partial d_j}{\partial \sigma_j} \\
&= -\left[\gamma \int_\tau^\infty x \phi_X(x)\, \mathrm{d}x\right] \frac{\partial \sigma}{\partial \sigma_j} - \left[\gamma \int_\tau^\infty \phi_X(x)\, \mathrm{d}x\right] \zeta \tau \frac{\partial \sigma}{\partial \sigma_i} \\
&= -\gamma \frac{\partial \sigma}{\partial \sigma_i} \left[\int_\tau^\infty (x + \zeta\tau) \phi_X(x)\, \mathrm{d}x\right]
\end{aligned}$$

where the last expression following using $\frac{\partial \sigma}{\partial \sigma_i} = \frac{\partial \sigma}{\partial \sigma_j}$. Because $E(X) = 0$ and $0 \leq \zeta < 1$,

$$\frac{\mathrm{d}W_i}{\mathrm{d}\sigma_j}\Big(x, \zeta = 1\Big) \leq \frac{\mathrm{d}W_i}{\mathrm{d}\sigma_j}\Big(x, \zeta\Big) \leq \frac{\mathrm{d}W_i}{\mathrm{d}\sigma_j}\Big(x, \zeta = 0\Big) < 0$$

Therefore, a small increase in σ_j is costly to individual i. ■

CHAPTER 3

Advanced methods make a difference: A case of the distribution of willingness to pay for advanced traveller information systems*

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Abstract

This paper uses stated preference data to analyse the distribution of willingness to pay for advanced traveller information systems and examine the implication of certain model assumptions on the estimated distribution of willingness to pay. A flexible estimation approach was used to estimate several models that vary in terms of restrictions embodied into them. Although simpler and relatively more advanced models yield nicely dispersed distribution for willingness to pay, this distribution ceased to exist when certain restrictions are set free in a more advanced model. The less restrictive model fitted the data better, and in this model, which combines the latent class and mixed logit models, it turns out that the data do not reveal any dispersion in willingness to pay. Results indicate that there is a group of travellers with zero willingness to pay and another group that has a positive willingness to pay. However, no dispersion of the willingness to pay was revealed within the second group. Findings in this study illustrate the importance of model specification testing, and that results regarding the estimated distribution of willingness to pay can be highly dependent on restrictions built into the model.

Keywords: willingness to pay; advanced traveller information systems; flexible distribution; intelligent transport systems; mixed logit; latent class

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1 Introduction

In an increasingly mobile 21st century society, there is growing demand for travel information. Travellers seek travel information as it can help them in decision making. It enables them to make better choice of travel options such mode, route and departure time. It is also demanded for network management. Advanced Traveller Information Systems (ATIS, henceforth) have a potential to serve this demand. These systems acquire, analyse and disseminate travel information which can improve driving experiences of individuals and enhance overall network performance. Amid increasingly unpredictable travel conditions ATIS could be of importance.

The current paper is concerned with estimating the distribution of willingness to pay for several types of information that an ATIS could provide. Evidence on the willingness to pay for ATIS is crucial in devising pricing strategies for its services and predicting market demand. It also supports in the decision to introduce new systems and/or expand existing ones (Stevens, 2004). Estimates of WTP may however depend on restrictions built into the empirical model. This paper examines the distribution of WTP for ATIS and the implication of certain restrictions embedded into the model on the estimated distribution of WTP.

The paper has several contributions. Firstly, in contrast to previous research on the WTP for ATIS (see Khattak *et al.* , 2003, for a review), the current paper examines the overall distribution of willingness to pay for more customised facets of information. Secondly, we employ a semi-nonparametric estimation approach (Fosgerau & Mabit, 2013) that allows for a more flexible shape for the underlying distribution of willingness to pay than the more commonly used estimation approaches, in which the shape of the distribution is pre-determined. We also extend the Fosgerau & Mabit approach to estimate a combined latent class – mixed logit model.

Analysis is based on data from a stated choice experiment designed to measure the willingness to pay for three types of information that an ATIS could provide: information about traffic accidents, congestion and roadworks. Each information type is expressed in terms of levels containing location, delay and routing information with varying frequency of updates. Data is collected using an internet questionnaire administered to 2000 respondents in Denmark.

We begin the analysis with a plain mixed logit model using a flexible distribution of willingness to pay. This results in a nicely dispersed distribution of willingness to pay, which however has a significant mass below zero. Negative willingness to pay, of course, does not make any sense in our context. The second model presented therefore allows for a point mass at zero. This model leads again to a nicely dispersed and positive distribution of willingness to pay for those with a non-zero willingness to pay.

Analysis might have stopped here with what could seem to be a plausible result. However, this model is very close to a latent class model comprising two classes: one consisting of subjects with zero willingness to pay and a second class consisting of people with non-zero willingness to pay. It embodies the restriction that the cost parameter is the same in the two classes. Relaxing this restriction, allowing for separate cost parameters in the two classes, has a drastic impact on results.

Relaxing the restriction on the cost parameters leads to a huge gain in log-likelihood of 700 log-likelihood points, so the less restrictive model clearly fits the data better. In this final model, it turns out that the data do not reveal any dispersion in the willingness to pay for ATIS. Thus, our findings regarding the distribution of willingness to pay were substantially affected by the last extension of the model. This illustrates the importance of model specification testing, and that results regarding the estimated distribution of willingness to pay can be highly dependent on restrictions built into the model.

The paper is organised as follows. Section 2 describes the stated choice experiment and data, while Section 3 and Section 4 outline the specification and estimation of the discrete choice model. Model estimates and discussion of results is presented in Section 5, followed by summary and conclusions in Section 6.

2 The Choice Experiment

The analysis is based on data from a stated choice survey designed to elicit willingness to pay for different types of information that an ATIS might provide. Data was collected using an internet questionnaire from respondents selected from an internet panel provided by Userneeds, a Danish panel company. Members of the panel are recruited voluntarily to create a sample representative of the population.

The survey targeted Danish residents with a driving license who had a car in the household for which they paid green owner tax. The green owner tax is an annual duty paid by car owners based on the vehicle's fuel efficiency aimed at reducing environmental damage. This tax provides a way to define the cost of alternative ATIS in the choice survey in reference to expenses incurred in real life.

Table 1: Attributes and their levels

Information types [t]	Information levels [ℓ]
Information about - [1] accidents - [2] roadworks - [3] congestion	[1] None [2] Location only [3] Location & duration of delays updated every hour [4] Location & duration of delays updated every 30 minutes [5] Location & duration of delays updated continuously [6] Continuous update of location and duration of delays and guidance to alternative routes
Cost	Levels of the cost attribute are pivoted around green owner tax at 0%, ±5%, -7%, ±10%, +15%, +23% and +33%

Moreover, the survey only considered those with recent driving experience so that options in the choice experiment are more accurately envisaged. One is considered as having a recent driving experience if he or she had driven a car in the 12 months preceding the time of the survey. The final analysis is based on 2000 individuals who completed the survey.

The survey presented each respondent with a choice between a pair of alternatives in a series of six choice situations. Each alternative is characterised by its cost and the level of three information types: information about traffic accidents, information about congestion and information about roadworks. Each information type is expressed in terms of one of six information levels as shown in Table 1. For every choice situation, the level of the cost attribute is chosen at random from 9 options that represent a 0%, 5%, 7% or 10% reduction in the green owner tax or a 5%, 10%, 15%, 23%, or 33% increase in this tax.

By construction, information levels are described in cumulative terms such that each higher level includes everything from the lower level. As more is likely to be better than less, we expect a higher information level would be more desirable. It is therefore straightforward to compare the relative desirability of different information levels associated with a given information type.

Table 2: A snapshot of a choice screen

Which alternative do you prefer?		
	Alternative A	Alternative B
Information about roadworks	Location and expected delays with continuous update	None
Information about congestion	Location and expected delays with update every half hour	Location only
Information about accidents	None	Location and expected delays with continuous update
Your green tax	DKK 2128	DKK 1440
	☐ Alternative A	☐ Alternative B

Table 2 shows a typical choice screen faced by a respondent who paid an annual green tax of DKK 1600.[1] In this choice situation, the respondent faced a choice between information contained in alternative 'A' with a 33% increase in his/her green owner tax and that contained in 'B' with a 10% reduction in green owner tax.

Table 3 shows the share of sample respondents by categories of respondent characteristics. Accordingly, more than three quarters of respondents are from households earning a gross annual income of DKK 0.2 million – DKK 1 million. As the survey targeted individuals in households owning at least one car, the sample is likely to over-represent respondents in more affluent households. Our survey slightly under-represents those in lower income groups compared to the Danish National Travel Survey (TU) data.

Since the survey targeted those with a driving license, each sample respondent was at least 18 years old - the minimum driving age in Denmark. Table 3 shows that about 75% of respondents are aged between 45-64 years. Compared to the TU data, the survey under-represents those in lower age brackets and over-represents those in the upper age brackets. The sample also consists of more males (62.7%) than females (37.3%); who are under-represented as compared to the TU data.

Moreover, the sample is not equally dispersed across different green tax levels with 50% of sample respondents paying DKK 1600 or DKK 3160 in green tax. This indicates the popularity of small and medium size petrol cars in Denmark.

[1] 1 Euro is about DKK 7.5

Table 3 also shows that about two in three respondents have full-time jobs (work at least 30 hours a week); 6.2% have part-time jobs (work 9-29 hours per week) while 16.6% are retired. The median respondent had encountered congestion or delays on at least 10% of his or her trips. Only a small proportion of sample respondents reported to have faced more frequent delays on their trip.

Table 3: Share of respondents by different covariates

Income[a]		Age (year)		Green tax (DKK)		Employment		Encounter delays	
Group	Share	Group	Share	Figure	Share	Status	Share	% Trips	Share
< 200	2.05	18-23	1.15	1600	23.75	Full time	65.85	5	37.4
200-399	17.40	24-34	6.85	3160	26.25	Part time	6.2	10	15.75
400-599	23.05	35-44	12.35	5760	6.20	Not working	4.9	15-30	24.1
600-799	25.25	45-54	29.75	2000	12.65	Retired	16.6	35-50	11.85
800-999	13.10	55-59	19.4	3300	18.40	Student	2.15	55-70	3.35
> 1000	6.90	60-64	25.45	5280	5.80	Others[c]	4.3	75-90	5.8
Others[b]	12.25	65-69	4.95	Others[c]	6.95			95-100	1.75

'Share' denotes percentage of sample respondents in each group
[a] Household income is in DKK'1000 per year
[b] These are records with missing income information
[c] Indicates labels other than those mentioned

3 Model Specification

When presented with a choice, respondents are assumed to evaluate the desirability of each alternative based on its attributes (Lancaster, 1966) and choose the one that provide them with the greatest utility. Let c be the cost of an alternative and $x_{t\ell}$ be the ℓ^{th} level of the t^{th} information type, where $t = 1, 2, 3$ and $\ell = 1, 2, \ldots, 6$ as shown in Table 1. Each $x_{t\ell}$ is coded as a dummy variable. The utility to person n from alternative i can be written as:

$$U_{ni} = -\theta c_{ni} + \tilde{\Gamma} X_{ni} + \varepsilon_{ni} \tag{1}$$

where $X = (x_{1\ell}, x_{2\ell}, x_{3\ell})_\ell$ is a vector of information levels, ε is a random error term and $\tilde{\Gamma} = (\tilde{\gamma}_{1\ell}, \tilde{\gamma}_{2\ell}, \tilde{\gamma}_{3\ell})_\ell$ and $\theta > 0$ are parameters of the model.

Willingness to pay for a particular information level $x_{t\ell}$ is the ratio of its coefficient and the cost coefficient: $\frac{\tilde{\gamma}_{t\ell}}{\theta}$. In principle one can model unobserved heterogeneity in willingness to pay by treating each of these ratios as a random variable. Practically however the resulting model would be intractable as it involves too many random parameters, one associated with the coefficient of each information level.

For computational tractability, we allow heterogeneity in the attitude towards overall services of ATIS while maintaining the weight of each information level constant across individuals. That is, while the degree of importance attached to ATIS can vary from individual to individual, the weight assigned to each information level is assumed constant across them. Incorporating this and re-parametrising the model to obtain willingness to pay estimates directly, the utility function can be written as:

$$U_{ni} = \theta \left[-c_{ni} + \theta \beta_n \Gamma X_{ni} \right] + \varepsilon_{ni} \tag{2}$$

where $\Gamma = (\gamma_{1\ell}, \gamma_{2\ell}, \gamma_{3\ell})_\ell$ and β_n is a willingness to pay index which captures the overall heterogeneity across individuals. This formulation is known as utility in willingness to pay space (Train & Weeks, 2005; Hensher & Greene, 2011; Hole & Kolstad, 2012). The willingness to pay for information level $x_{t\ell}$ is now $\beta_n \gamma_{t\ell}$. The shape of the distribution of willingness to pay is the same for all information levels; it is the scale of the distribution that varies across information levels.

Suppose ε is *i.i.d.* type-one extreme value distribution with mean 0 and constant variance $\frac{\pi^2}{6}$. In the first model, Model A, we assume that β is *i.i.d.* across individuals with a continuous distribution function Φ. Denoting by $\boldsymbol{i}$ the event that alternative i is chosen in each of the $q = 1, 2, \ldots, 6$ choice situations, an individual's contribution to the likelihood will be

$$P_n \left(\boldsymbol{i} | Z_n, \Gamma, \theta \right) = \int G \left(Z_n, \Gamma, \theta, \beta_n \right) \phi \left(\beta_n \right) \mathrm{d}\beta_n \tag{3}$$

where $Z_n = (c_n, X_n)$; $G\left(Z_n, \Gamma, \theta, \beta_n\right) = \prod_q g\left(Z_{niq}, \Gamma, \theta, \beta_n\right)$ is the choice probability in a sequence of choice situations where $g\left(\Gamma\theta, \beta_n\right)$ is the choice probability of the binary logit model conditional on β.

Though this model leads to a nicely dispersed distribution of willingness to pay, the distribution however has a significant mass below zero. The estimated willingness to pay assumes negative values for a non-trivial share of the sampled population. Since negative willingness to pay does not make sense, a point mass at zero is allowed in order to restrict willingness to pay within a permissible range.

The next model, Model B, allows for a point mass at zero by assuming that the sample is drawn from a population consisting of two latent classes. In the first class ($k = 1$) are individuals who attach importance to information attributes, while the second class ($k = 2$) consists of those who deemed these attributes are unimportant. Subsequently, the distribution of β among individuals in the first class is estimated, while $\beta = 0$ is maintained in the second class.

At this point, we have two layers of heterogeneity - a continuous variation of willingness to pay within the first class and a discrete segmentation of the sample into the two classes. To capture both within and across class heterogeneity, we used a mixed logit latent class model (Bujosa *et al.* , 2010; Greene & Hensher, 2012). This model combines the merits of both the latent class and the continuous mixture models.

Suppose that class membership probabilities are independent of Z. If π_k denotes the probability of membership of the k^{th} class for $k = 1, 2$, and f is the density of β in the first class, the choice probability in a sequence of choice situations will be

$$P_n\left(\boldsymbol{i}|Z_n, \Gamma, \theta, \pi_2\right) = \pi_2 G\left(Z_n, \theta, \beta_n = 0\right) + \left(1 - \pi_2\right) \int G\left(Z_n, \Gamma, \theta, \beta_n\right) f\left(\beta_n\right) \mathrm{d}\beta_n \tag{4}$$

Since class membership probabilities must add up to one, π_2 is estimated with $\pi_1 = 1 - \pi_2$. Hence, π_2 indicates the probability of a zero willingness to pay as opposed to a non-zero amount. Except allowing for a point mass at zero this model is equivalent to Model A.

Model B embodies the restriction that the cost parameter is equal for the two classes. Generally, however, the parameter could differ between the classes indicating class-specific responsiveness to the cost attribute. Model B is thus extended to allow for class-specific cost parameters. An individual's contribution to the likelihood in this model, labelled Model C, is

$$P_n\left(\boldsymbol{i}|Z_n, \Gamma, \theta_1, \theta_2, \pi_2\right) = \pi_2 G\left(Z_n, \theta_2, \beta_n = 0\right) + \left(1 - \pi_2\right) \int G\left(Z_n, \Gamma, \theta_1, \beta_n\right) f\left(\beta_n\right) \mathrm{d}\beta_n \tag{5}$$

which is similar to Model B except that it allows for class specific cost parameters.

4 Estimation

Since the choice probabilities in (3)-(5) allow no analytical expression, estimation is performed using maximum simulated likelihood (Train, 2003). In most empirical applications, estimation proceeds by specifying a distribution for the random parameter and simulating choice probabilities based on draws from this distribution. Therefore, prior knowledge of the distribution is required to perform simulation.

It has been shown that estimates of willingness to pay from parametric models can be sensitive to the assumed distribution, and that the choice of an inappropriate distribution leads to bias (Hess *et al.* , 2005; Fosgerau & Bierlaire, 2007). Given our interest in the distribution per se, it is imperative to mitigate the risk of bias as a result of the assumed shape of the distribution. Most importantly, it is undesirable to impose the shape of the distribution when one seeks to estimate the distribution as such.

In this paper, we employed a semi-nonparametric estimation approach proposed by Fosgerau & Mabit (2013) that allows a more flexible distribution for the random parameter. As opposed to specifying an ex ante distribution, this approach asserts that the distribution of a random parameter can be simulated given deep parameters that are estimated along with other parameters of the model. This approach is simple to implement and it can approximate essentially any distribution.

Under this approach, simulation is performed using draws of the random parameter computed based on draws from any distribution and transforming these draws using a polynomial series. To illustrate, suppose $u = (u_1, u_2, \ldots, u_R)$ is a vector of R independent draws from a standardised uniform distribution, $\mathcal{U}(0, 1)$; and that u is uncorrelated with other covariates in the model. Then, a draw of the random parameter is computed as

$$\beta^{(r)} = \sum_{m=0}^{M} \alpha_m u_r^m \tag{6}$$

where $m = 0, 1, 2, \ldots, M$ and $\alpha = (\alpha_0, \alpha_1, \ldots, \alpha_M)$ is a vector of deep parameters estimated along with other parameters of the model. The likelihood is simulated conditional on draws computed in (6).

Though a polynomial of higher degree provides more flexibility in shape, it however poses a serious problem in estimation by inducing correlation among different terms of the polynomial. Even with a polynomial of degree 2 based on draws u from a standard uniform distribution, the correlation between the terms u and u^2, is 0.97. The problem of correlation can be reduced by using orthogonal polynomials (Fosgerau & Mabit, 2013).

We use orthonormal Legendre polynomials proposed by Bierens (2008). These polynomials are mutually orthogonal in the interval $[0,1]$, *i.e.*,

$$\int_0^1 L_m(u)L_{m'}(u)\,\mathrm{d}u = \begin{cases} 0 \text{ if } m \neq m' \\ 1 \text{ if } m = m' \end{cases} \tag{7}$$

where $L_m(u)$ is the m^{th} Legendre polynomial on u defined recursively by

$$L_m(u) = \frac{\sqrt{4m^2-1}}{m}(2u-1)\,L_{m-1}(u) - \frac{(m-1)\sqrt{2m+1}}{m\sqrt{2m-3}}L_{m-2}(u) \tag{8}$$

starting from $L_0(u) = 1$ and $L_1(u) = \sqrt{3}\,(2u-1)$. Given orthogonal Legendre polynomials, the r^{th} draw of β is now computed as

$$\beta^{(r)} = \sum_{m=0}^{M} \alpha_m L_m(u) \tag{9}$$

which is used in simulation instead of the draws u

Given α and R draws of β, the cumulative distribution of β is approximated by $F(\lambda) \simeq \frac{1}{R}\sum_{r=1}^{R} 1\left\{\beta_n^{(r)} < \lambda\right\}$ where the summand equals 1 if the expression inside the curly brackets is true or 0 otherwise.

The shape of the estimated willingness to pay distribution is determined by the number of deep parameters specified. Each model is estimated by specifying varying number of deep parameters to achieve more flexibility in the estimated distribution; estimation results are shown in Appendix A.

For a given M, Models A, B and C are nested. Model A is a restricted version of Model B with the restriction being $\pi_2 = 0$; and Model B is a special case of Model C where $\theta_1 = \theta_2$ is maintained. For each model, the best specification regarding the degree of the approximating polynomial is chosen based on the likelihood ratio test. It turns out that the best specification for these models is associated with different degrees of approximating polynomials.

For different degrees of approximating polynomials, Models A, B and C are non-nested. Subsequently, the Bayesian Information Criterion (BIC) is used to test for model selection among these models. The BIC is defined as $\text{BIC} = -2\mathcal{L} + d_f \ln(N)$ where N is the number of observations, $\mathcal{L}$ is the value of log-likelihood at convergence and d_f is the number of degrees of freedom. Accordingly, the model with the least BIC value is preferred.

All models are estimated on the full sample of 2,000 individuals using 1,000 Halton draws in Biogeme (Bierlaire, 2003). Estimates remain stable for changes in starting values and the number of draws in estimation. Assuming that an individual's preferences are constant over a sequence of choice situations, the same draws are used for a sequence of choices belonging to a given individual.

For numerical reasons, the level of the cost attribute is divided by 100 with estimated willingness to pay figures expressed in DKK 100 per year. For each information type t, the information level 'None' is taken as a base category with the corresponding γ_{t1} normalised to zero. Moreover, γ_{12} is normalised to one to provide identification.

To test whether there was a tendency of respondents choosing the option on the same side of the choice screen to simplify decision making, a dummy was included for the left-hand side alternative. Based on the preferred specification under Model A, we did not find evidence supporting this tendency. Moreover, since alternatives in the choice set are unlabelled, in the sense that they all represent virtual ATIS, neither alternative specific coefficients nor alternative specific constants are relevant in our analysis.

5 Results and Discussion

Table 4 shows the preferred set of estimates under Models A, B and C along with estimates from a corresponding binary logit model. For Model A, though specifications based on the fifth and sixth degree polynomials outperform the specification based on the fourth degree polynomial, the latter is preferred as estimates of certain target coefficients under the former become statistically insignificant. For Model B, since the specification based on the sixth and higher degree polynomials failed to converge, the specification based on the fifth degree polynomial is preferred. For Model C, the specification based on the first degree approximating polynomial is chosen since it outperforms specifications based on higher degree polynomials.

In all models, estimates of π_2, each $\gamma_{t\ell}$ and the cost parameters are statistically significant and have the expected positive sign. Moreover, all the estimated polynomial coefficients, except for α_1 under Model C, are significant. The values of log-likelihood indicate that Model C provided a much higher improvement in model fit compared to all other models. It provided an impressive 700 additional log-likelihood units compared to

Model B. The overall fit of Model C is a significant improvement over all other models based on the BIC index; according to which Model B outperforms Model A, and the latter is preferred to the binary logit model.

Table 4: Preferred set of estimates from alternative models

	Binary logit		Model A		Model B		Model C	
	Estimate	t-stat	Estimate	t-stat	Estimate	t-stat	Estimate	t-stat
γ_{13}	0.61	7.48	0.99	11.58	0.95	5.81	0.90	13.34
γ_{14}	0.90	11.03	1.22	8.25	1.17	4.51	1.17	16.79
γ_{15}	0.95	11.09	1.53	11.77	1.62	8.94	1.31	17.98
γ_{16}	1.37	14.13	1.83	10.45	1.89	7.69	1.62	16.95
γ_{22}	0.15	2.28	0.51	4.74	0.50	4.31	0.55	8.83
γ_{23}	0.48	6.16	0.86	5.39	0.90	8.38	0.81	10.92
γ_{24}	0.50	6.22	1.04	5.10	1.17	7.37	0.70	9.53
γ_{25}	0.47	5.72	0.93	4.87	1.06	6.46	0.70	9.40
γ_{26}	0.66	6.91	1.49	5.90	1.67	10.50	1.12	12.16
γ_{32}	0.63	8.42	0.93	3.88	1.08	15.07	0.84	12.25
γ_{33}	0.70	8.83	1.08	5.13	1.23	10.47	0.80	12.02
γ_{34}	0.71	7.91	1.56	4.33	1.82	8.96	1.07	12.85
γ_{35}	1.06	11.09	1.59	6.11	1.73	9.57	1.15	13.31
γ_{36}	1.05	10.86	1.65	5.29	1.85	6.23	1.42	15.20
θ	0.16	37.74	0.19	20.63	0.19	24.64		
θ_1							0.06	7.91
θ_2							0.78	10.28
π_2					0.73	22.80	0.53	23.80
α_0	4.42	15.66	5.16	7.86	31.70	2.60	19.60	7.50
α_1			6.12	9.33	34.60	2.08	$0.00^{\dagger}$	$0.00^{\dagger}$
α_2			5.98	8.95	38.60	2.40		
α_3			4.65	7.50	29.80	2.38		
α_4			2.98	4.68	20.10	2.48		
α_5					11.60	3.58		
$\mathcal{L}$	-6669.39		-6526.78		-6506.23		-5809.06	
d_f	16		20		22		19	
BIC	13489.06		13241.42		13219.10		11796.59	
Obs.	12000		12000		12000		12000	

† Assumes zero for several digits after the decimal.

Results in Table 4 indicate that, in general, a higher willingness to pay is estimated for more desirable information levels and for information about accidents and congestion. The attribute level containing real-time location, delay and routing information has the highest estimated weight, which when averaged across the three information types exceeds the estimated weight of the attribute level containing real-time location and delay information by over 25%. Weights of the two information levels signify the importance of guidance to alternative routes over and above real-time delay and location information (Kim & Vandebona, 1999).

In some cases, however, the estimated ranking of information levels is inconsistent. In most cases where this is true, the difference between the relevant coefficients is insignificant. The anomalous ranking could be caused by the inability to fully process the differences between some of the information levels.

For a given information level, weights assigned to different information types indicate their relative importance. In general, estimates suggest a higher willingness to pay for information about congestion and accidents than for information about roadworks. This is conceivable considering the fact that plans for road construction and maintenance are often advertised through media and roadside posters hence are hardly 'news' to drivers.

The implied distribution of willingness to pay is simulated conditional on parameter estimates in Table 4. Since the binary logit model does not permit unobserved heterogeneity, the willingness to pay index, β, under this model corresponds simply to α_0. This model is a special case of Model A where all coefficients, except the constant α_0, of the polynomial approximation of ϕ are constrained to zero.

For Models A, B and C, the willingness to pay index is allowed to vary in the population. Conditional on estimates of deep parameters, the implied distribution of the willingness to pay index is simulated using 1,000,000 random draws. The cumulative probability distribution curve of simulated willingness to pay indexes is depicted in Figure 1; while the mean and some quantiles of the simulated distribution are shown in Table 5.

Under Model A, the estimated distribution is nicely dispersed and right-skewed. The model predicted a higher probability for lower values of willingness to pay and a positive probability for negative values of the willingness to pay. As is apparent in Figure 1, the estimated distribution has a considerable mass below zero with more than one in five simulated willingness to pay values being negative. Given our expectation of a non-negative willingness to pay, we conclude that this model is misspecified.

Model B overcomes this misspecification by allowing for a point mass at zero. It

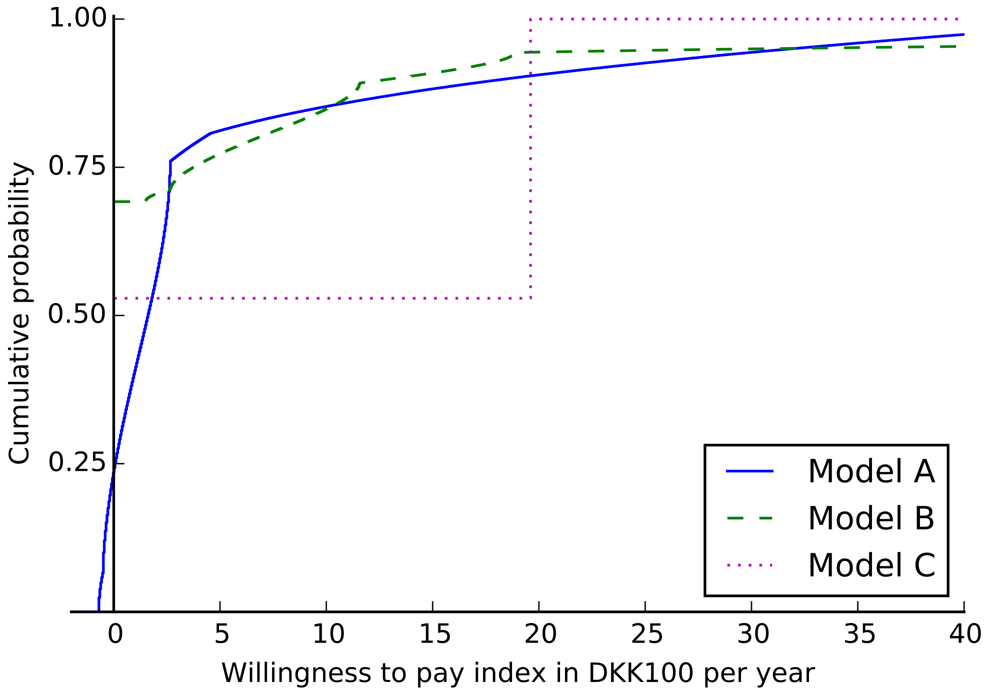

Figure 1: Simulated cumulative distribution curves of willingness to pay index

restricted willingness to pay values to a non-negative interval, and predicted a higher (72.5%) probability for having a zero willingness to pay which corresponds to the height of the spike at zero. This indicates that a greater proportion of sampled individuals are unwilling to pay for travel information. This disinclination to pay for ATIS is consistent with previous empirical literature (Polydoropoulou *et al.* , 1997; Kim & Vandebona, 1999; Wolinetz *et al.* , 2001; Khattak *et al.* , 2003) who gave evidence for a low willingness to pay for ATIS. Over a common support, the shape of the distribution of willingness to pay under Model B is comparable to that under Model A. In both bases, the distribution rises rapidly before it flattened out to the right.

Model C relaxed a restriction under Model B by allowing for separate cost parameters in the two classes. The difference between the estimates of the two cost parameters is significant implying that those unwilling to pay for travel information are more sensitive to the cost of ATIS.

Allowing for separate cost parameters in the two classes led to a huge improvement in log-likelihood of 700 log-likelihood units, so Model C clearly fits the data better. Model

Table 5: Certain features of willingness to pay index distribution

	Mean	Quantiles						
		5%	10%	25%	50%	75%	90%	95%
Model A	5.16	-0.57	-0.44	0.09	1.64	2.68	18.68	31.95
Model B	9.72	0	0	0	0	3.75	13.23	30.37
Model C	9.24	0	0	0	0	19.61	19.61	19.61

Values are in DKK 100 per year

C is also preferred to Model B based on the BIC. The extension in this model, that the cost parameter is allowed to differ between the two classes, had a drastic impact on the estimated distribution.

In this final model, the data does not reveal any dispersion in willingness to pay across those willing to pay a non-zero amount. This is apparent from the estimate of α_2, which is too small to induce any meaningful variation in willingness to pay within the population. This suggests that the nicely dispersed distribution of willingness to pay from Model B is a result of the assumed homogeneity of the cost parameter in the two classes.

In essence, Model C is reduced to a fixed parameter latent class model. As such, the model led to a discrete distribution for willingness to pay. Estimates indicate a probability of 53% that willingness to pay equals zero and a probability of 47% that it takes the fixed estimated non-zero value. Thus, our findings regarding the distribution of willingness to pay were very substantially affected by the last extension of the model.

The analysis regarding the distribution of willingness to pay has several implications. Firstly, it illustrates the importance of model specification testing. Had we not allowed for and subsequently tested the possibility of a separate cost parameter between the two classes, our conclusion regarding the distribution of willingness to pay would have been based on estimates from Model B. However, results in Model C indicate that the seemingly dispersed distribution of willingness to pay from Model B is purely spurious, and is induced by the imposition of equal cost parameters in the two classes.

Secondly, the analysis also illustrates that our conclusion regarding the estimated distribution of willingness to pay can be highly dependent on restrictions built into the model. Though several models are estimated, some more general than others with regard to assumptions embedded, neither one of them produced results consistent with the other.

An unbounded distribution in Model A caused a misspecification; Model B addressed the misspecification and led to a seemingly dispersed distribution of willingness to pay, which ceased to exist once Model C allowed for separate cost coefficients in the two classes.

6 Summary and Conclusion

Based on data acquired by means of a stated choice survey from 2,000 drivers in Denmark, this paper reports results from the analysis of the distribution of willingness to pay for an ATIS which could provide location, delay and routing information about three causes of unpredicted travel delays: traffic accidents, roadworks and congestion.

The analysis, in general, indicates that a significant share of drivers have a zero willingness to pay for ATIS, and that among those willing to pay a non-zero amount, the willingness to pay is distributed fairly tightly. Moreover, the willingness to pay for information about congestion and traffic accidents is higher than that for information about roadworks.

The distribution is estimated employing a discrete choice model in which willingness to pay is treated as a random variable. Analysis began with a simple mixed logit model using a flexible unbounded distribution of willingness to pay. This resulted in a nicely dispersed distribution of willingness to pay, which however had significant mass below zero.

We therefore allowed for a point mass at zero in a subsequent mixed logit-latent class model in order to address the misspecification. In this model, the sample is assumed to have been drawn from a population comprising of one group (class) of subjects with zero willingness to pay and another group with a non-zero willingness to pay. This model led again to a nicely dispersed and positive distribution of willingness to pay for those with non-zero willingness to pay.

This seemingly plausible result, however, ceased to exist when an assumption embedded in the model, namely that the cost parameter is the same in the two classes, was relaxed in a subsequent model. In this final model, wherein separate cost parameters are allowed in the two classes, the data does not reveal any dispersion of the willingness to pay for ATIS among those willing to pay a non-zero amount. This indicates that our conclusions in the previous model were affected by restrictions on the cost parameters.

The analysis illustrates the importance of model specification testing, and that results regarding the estimated distribution of willingness to pay can be highly dependent on restrictions built into the model. When inferring behavioural values such as willingness to pay, we shall therefore be alert to the possibility that seemingly plausible results from simpler (and even fairly advanced) models could be driven by restrictions embedded in these models. Though results from simpler models seemed manifested by the data, it is essential to thoroughly examine how much they rely on restrictions.

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A Appendix

Table 6: Estimates from Model A with varying degrees of approximating polynomials

	$M=1$		$M=2$		$M=3$		$M=4$		$M=5$		$M=6$	
	Est.	t-val	Est.	t-val	Est.	t-val	Est.	t-val	Est.	t-val	Est.	t-val
γ_{13}	0.89	7.31	0.96	11.88	0.97	11.73	0.99	11.58	1.02	7.95	1.07	1.37
γ_{14}	1.16	8.73	1.19	10.89	1.20	8.76	1.22	8.25	1.23	8.34	1.27	1.05
γ_{15}	1.39	13.45	1.46	16.78	1.50	17.12	1.53	11.77	1.56	5.18	1.62	2.75
γ_{16}	1.65	8.89	1.73	14.15	1.76	14.84	1.83	10.45	1.90	3.98	2.03	1.96
γ_{22}	0.54	6.55	0.56	7.16	0.52	6.89	0.51	4.74	0.53	1.44	0.63	1.02
γ_{23}	0.89	7.59	0.92	8.83	0.88	8.04	0.86	5.39	0.85	1.65	0.92	1.44
γ_{24}	1.10	8.37	1.11	8.63	1.05	7.71	1.04	5.10	1.06	1.56	1.15	4.03
γ_{25}	0.96	8.04	1.00	10.07	0.96	9.01	0.93	4.87	0.93	1.34	1.05	1.31
γ_{26}	1.36	9.12	1.49	11.09	1.48	10.08	1.49	5.90	1.53	2.16	1.70	3.50
γ_{32}	0.97	6.98	0.99	7.90	0.96	5.90	0.93	3.88	0.95	2.33	1.02	3.44
γ_{33}	1.09	8.43	1.14	9.65	1.11	8.59	1.08	5.13	1.08	1.94	1.15	4.12
γ_{34}	1.48	8.35	1.57	8.91	1.57	7.35	1.56	4.33	1.58	1.64	1.68	3.85
γ_{35}	1.49	10.54	1.57	10.80	1.59	9.39	1.59	6.11	1.62	2.69	1.73	10.30
γ_{36}	1.57	11.63	1.63	10.92	1.64	9.05	1.65	5.29	1.68	2.06	1.84	1.98
θ	0.18	23.70	0.19	22.72	0.19	21.91	0.19	20.63	0.19	15.73	0.20	10.36
α_0	3.83	8.91	4.52	9.73	4.90	9.19	5.16	7.86	5.39	8.26	6.18	1.37
α_1	5.98	12.35	5.87	12.40	5.97	11.16	6.12	9.33	6.51	3.28	6.60	0.84
α_2			4.68	12.93	5.39	12.05	5.98	8.95	6.48	4.30	8.92	1.24
α_3					3.74	10.61	4.65	7.50	5.48	2.69	6.56	0.83
α_4							2.98	4.68	4.00	1.44	7.22	1.44
α_5									1.87	0.90	3.51	0.82
α_6											3.49	1.92
$\mathcal{L}$	-6620.09		-6563.86		-6536.82		-6526.78		-6524.46		-6520.43	
d_f	17		18		19		20		21		22	
BIC	13399.85		13296.80		13252.09		13241.42		13246.16		13247.50	
Obs.	12000		12000		12000		12000		12000		12000	

Table 7: Estimates from Model B with varying degrees of approximating polynomials

	$M=1$		$M=2$		$M=3$		$M=4$		$M=5$	
	Est.	t-stat	Est.	t-stat	Est.	t-stat	Est.	t-stat	Est.	t-stat
γ_{13}	0.99	11.37	1.03	1.37	0.93	7.72	0.93	8.85	0.95	5.81
γ_{14}	1.19	9.03	1.23	1.13	1.10	6.52	1.12	6.81	1.17	4.51
γ_{15}	1.54	15.70	1.73	1.05	1.62	12.19	1.61	14.18	1.62	8.94
γ_{16}	1.79	13.11	2.04	1.30	1.89	11.09	1.87	12.71	1.89	7.69
γ_{22}	0.53	7.10	0.58	5.05	0.50	6.10	0.48	6.80	0.50	4.31
γ_{23}	0.90	8.13	0.94	5.33	0.89	12.24	0.89	13.70	0.90	8.38
γ_{24}	1.07	7.69	1.32	0.81	1.22	8.53	1.17	11.18	1.17	7.37
γ_{25}	1.00	10.08	1.10	1.18	1.05	9.97	1.04	11.62	1.06	6.46
γ_{26}	1.54	11.24	1.70	2.67	1.66	15.33	1.65	16.68	1.67	10.50
γ_{32}	1.03	6.96	1.17	1.36	1.12	16.79	1.08	18.00	1.08	15.07
γ_{33}	1.17	8.68	1.34	0.98	1.25	12.76	1.22	14.78	1.23	10.47
γ_{34}	1.68	7.85	2.04	0.80	1.87	10.83	1.81	13.36	1.82	8.96
γ_{35}	1.66	9.21	1.88	1.42	1.75	12.72	1.71	13.34	1.73	9.57
γ_{36}	1.73	9.28	2.02	0.87	1.84	8.67	1.81	9.26	1.85	6.23
π	0.75	25.68	0.75	1.93	0.75	26.16	0.73	22.80	0.69	13.70
θ	0.19	23.89	0.19	16.47	0.19	24.56	0.19	24.64	0.19	24.57
α_0	17.30	8.55	20.20	0.41	27.20	4.05	31.90	3.93	31.70	2.60
α_1	10.00	8.61	15.50	0.32	25.30	3.20	33.80	3.25	34.60	2.08
α_2	0	0	10.30	0.50	21.10	3.72	31.90	3.46	38.60	2.40
α_3	0	0	0	0	11.20	4.74	22.50	3.89	29.80	2.38
α_4	0	0	0	0	0	0	11.70	4.48	20.10	2.48
α_5	0	0	0	0	0	0	0	0	11.60	3.58
$\mathcal{L}$	-6537.85		-6526.601		-6515.197		-6508.709		-6506.231	
d_f	18		19		20		21		22	
BIC	13244.76791		13231.66258		13218.24724		13214.6639		13219.10056	
Obs.	12000		12000		12000		12000		12000	

Table 8: Estimates from Model C with varying degrees of approximating polynomials

	$M = 1$		$M = 2$		$M = 3$		$M = 4$	
	Est.	t-stat	Est.	t-stat	Est.	t-stat	Est.	t-stat
γ_{13}	0.90	13.34	0.90	13.35	0.90	13.35	0.90	13.35
γ_{14}	1.17	16.79	1.17	16.79	1.17	16.79	1.17	16.79
γ_{15}	1.31	17.98	1.31	18.01	1.31	18.01	1.31	18.01
γ_{16}	1.62	16.95	1.62	16.96	1.62	16.96	1.62	16.96
γ_{22}	0.55	8.83	0.55	8.83	0.55	8.83	0.55	8.83
γ_{23}	0.81	10.92	0.81	10.91	0.81	10.91	0.81	10.91
γ_{24}	0.70	9.53	0.70	9.54	0.70	9.54	0.70	9.54
γ_{25}	0.70	9.40	0.70	9.41	0.70	9.41	0.70	9.41
γ_{26}	1.12	12.16	1.12	12.16	1.12	12.16	1.12	12.16
γ_{32}	0.84	12.25	0.84	12.24	0.84	12.24	0.84	12.25
γ_{33}	0.80	12.02	0.80	11.99	0.80	11.99	0.80	12.00
γ_{34}	1.07	12.85	1.07	12.86	1.07	12.86	1.07	12.85
γ_{35}	1.15	13.31	1.14	13.30	1.14	13.30	1.14	13.30
γ_{36}	1.42	15.20	1.41	15.19	1.41	15.19	1.41	15.19
π	0.53	23.80	0.53	23.76	0.53	23.76	0.53	23.77
θ_1	0.78	10.28	0.78	10.26	0.78	10.26	0.78	10.27
θ_1	0.06	7.91	0.06	7.90	0.06	7.90	0.06	7.90
θ_2	0.78	10.28	0.78	10.26	0.78	10.26	0.78	10.27
α_0	19.60	7.50	19.60	7.50	19.60	7.50	19.60	7.50
α_1	-1.5e-3	0.00	-5.2e-6	0.00	2.25e-06	0.86	-4.2e-06	-0.58
α_2			1.20	0.67	1.20	0.67	1.18	0.72
α_3					0.00	-0.77	0.00	0.80
α_4							-0.39	-0.33
$\mathcal{L}$	-5809.06		-5809.02		-5809.02		-5809.02	
d_f	19		20		21		22	
BIC	11796.59		11805.90		11815.29		11824.68	
Obs.	12000		12000		12000		12000	

CHAPTER 4

The effect of a firm's relocation distance on worker turnover: Evidence from Denmark

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Abstract

Firm relocation can induce job mobility decisions through its effect on the commuting distance for workers. Using Danish register data, we investigate the effect of relocation distance on worker turnover at the firm level. We find a positive and significant but moderate effect. Results in the paper establish that, on average, a 10 km increase in relocation distance leads to a 2–4 percent increase in the annual rate of worker turnover at the firm level over three years, including the year of relocation. Results also show that firms having a higher share of male, more experienced and higher educated workers face lower worker turnover, as do firms located closer to their workers.

Keywords: worker turnover; firm relocation; job mobility; commuting distance.

JEL classification: J63; R41.

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1 Introduction

Firm relocation affects the commute patterns for existing workers. In fact, the sustained trend of firm relocation farther from residences, and often towards suburbs, has increased the average commute distance for workers (Kneebone & Holmes, 2015). The time and money costs of increased commuting can influence the choice of residential location (e.g. Zax, 1991; van Ommeren *et al.* , 1999; Clark *et al.* , 2003), job search location (e.g. Immergluck, 1998; Kneebone & Holmes, 2015), travel mode as well as car ownership decisions. Most importantly for the purpose of this paper, firm relocation can also induce job mobility due to high costs of residential mobility and long distance commuting.

Past research suggests that job mobility decisions are partly motivated by commuting distance considerations (Levinson, 1997; Immergluck, 1998). This paper examines the extent to which the relocation distance of moving firms is related to worker turnover. Despite past research on the effect of commuting distance on job moving behaviour (e.g. van Ommeren *et al.* , 1999; Clark *et al.* , 2003; Deding *et al.* , 2009), analysis has typically been at the individual worker level.[1] As a result, little is known about the nature and extent of this relationship at the firm level. Investigating the relationship at the firm level is essential as it shows the aggregated effect of various individual-level decisions. Besides, since the effect of relocation on job mobility decisions is likely to depend on relocation distance, it is not until this effect is quantified that employers of moving firms can control worker turnover, a key indicator of the firm's costs of hiring and training workers, through an optimally chosen relocation distance.

Conceivably, the effect of relocation on worker turnover depends on whether, and how far, the firm moves closer to its workers. If residences are concentrated and a firm moves towards its workers, then the relocation shortens commutes to all workers. When this is the case, the relocation distance is unlikely to induce job mobility unless the pre-relocation commute distance was optimally chosen and that, any deviation from that is undesirable. In most cases, however, relocation has losers and winners since it shortens the commuting distance for some workers while lengthening the commutes for others. For those who lost

[1]A notable exception is Zax & Kain (1996) who studied the effect of relocation distance on job mobility based on data from a single firm. As opposed to them, we considered the entire population of firms in Denmark.

from relocation, longer relocation distance leads to longer commutes suggesting a positive relationship between relocation distance and worker turnover.

One may argue that employers can contemplate the effect of relocation distance on workers and that they would offer compensation in order to keep their important employees. To the extent this argument holds, the relationship between relocation distance and worker turnover may not be as hypothesised. However, we believe that the hypothesised positive relation holds due to the following reasons. Firstly, firms may not be willing to compensate workers in all situations. Secondly, although employers compensate workers for commuting costs, evidence suggests that workers are only partially compensated (Manning, 2003; Mulalic *et al.* , 2013). Moreover, even when employers pay higher wages to prevent workers from leaving, some workers may have to move residence to stay with the firm. However, this may not be possible due to factors that restrict residence mobility such as social attachment to places (Dahl & Sorenson, 2010); or due to high costs of moving residences. In such circumstances, job mobility is a more feasible option to reduce commuting distances.

The analysis in the current paper is based on matched employer-employee information from Danish register-based data for the years 2000–2007. The dataset consists of the entire population of firms and their employees. A characteristic feature of the Danish labour market is the high rate of job mobility. Every year, about 25 percent of workers in the labour force move jobs (Albak & Sørensen, 1998; Commission, 2006; Eriksson & Westergaard-Nielsen, 2009), a rate which is high even by OECD standards. It can therefore be costly for firms to lose additional workers due to long distance relocation, given the high rate of worker mobility.

Estimation is performed on a combined sample of relocated and non-relocated firms by including a dummy indicator for relocation. This is done to examine whether relocation distance captures the effect of the firm's relocation per se, and possible restructuring that follows. Our estimates indicate that, after controlling for relocation distance, there is no significant difference in worker turnover between relocated and non-relocated firms. Therefore, relocation distance is not picking up the effect of firm relocation as such.

We find a moderate but significant effect of relocation distance on worker turnover. Results in the paper establish that, on average, a 10 km increase in relocation distance leads to a 2–4 percent increase in the annual rate of worker turnover at the firm level over a period of three years, including the year of relocation. The estimated effect is stronger in the first year after relocation and pales away after the third year as workers more or less fully adjust to the change. The effect in the year of relocation is expected to be smaller as some firms could have relocated late in the year allowing little time for workers to adjust. The fact that we obtain a significant effect could suggest that workers probably knew about the relocation decision ahead of time, such that they could search other jobs and move before or soon after the firm relocated.

Besides relocation distance, our model includes various pre-relocation characteristics as additional controls. These are firm related features and worker characteristics aggregated at the firm level. One such control variable is the average commuting distance of workers in a firm, for which we obtain a significant, positive coefficient indicating that, on average, firms that are located farther from their employees face higher worker turnover. Interestingly, this coefficient is in the same order of magnitude as the coefficient associated with relocation distance. The analysis also show that firms with a higher share of workers having children face, on average, lower worker turnover. Results also show that firms having a higher share of male, more experienced and higher educated workers face lower worker turnover, as do firms located closer to their workers.

The rest of the paper is organised as follows. Section 2 describes two important variables in the analysis: measures of worker turnover and a firm's relocation distance. In Section 3, we outline a description of the data as well as summary statistics on important variables. Section 4 shows estimation results and discusses findings from the analysis. We carry out a sensitivity analysis in Section 5 while the last section concludes.

2 Worker turnover and relocation distance

2.1 Relocation distance

We do not have information about the move distance of relocated firms readily available in the data. Neither were we able to infer this information from firm and residence addresses since street names (and numbers) are not provided in the data to protect worker and firm privacy. Therefore, we do not have the true distance of relocation. We estimate the distance of firm relocation as follows. First, we observe the relocation status of a firm based on over-the-year change in its registered address.[2] Since the commuting distances of workers for the shortest route between residence and workplace location is provided, we use this information to compute the move distance of relocated firms. Figure 1 illustrates the use of the available information to derive information on relocation distance.

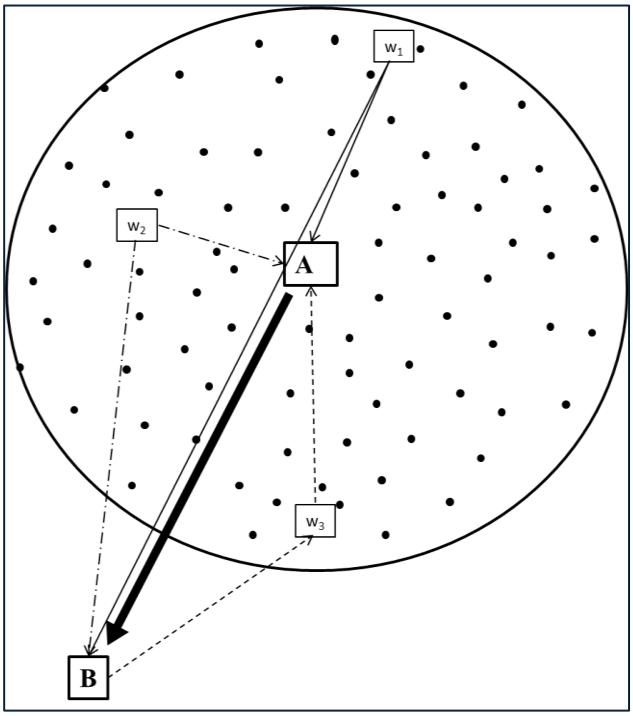

Figure 1: Computation of a firm's relocation distance

Assume that worker residences are distributed in the space surrounding the firm. We focus on workers who did not change employer and residence during the base year. This ensures that changes in commuting distance are due to the firm relocation and not caused by residential relocation or a job change. Now consider the example illustrated in Figure 1. In this figure, we consider the relocation distance of a firm that relocated from point A to B. It is easy to see that the longest (absolute) change in worker commuting distance (in our figure for worker w_1) is a good candidate for the estimate of the firm's relocation distance and it is always a lower bound for this distance.[3] We estimate a firm's relocation distance using the largest absolute change in worker commuting distance. To test for robustness of our estimate, we re-compute the measure of relocation distance after removing observations

[2]We observe a pseudo, not actual address of firms and residence locations.

[3]Since this measure of relocation distance can be affected by firm size, we have controlled for the number of workers and excluded small firms from the analysis.

with the largest absolute change in commuting distance. Our results turn out to be stable suggesting that the measure is robust.

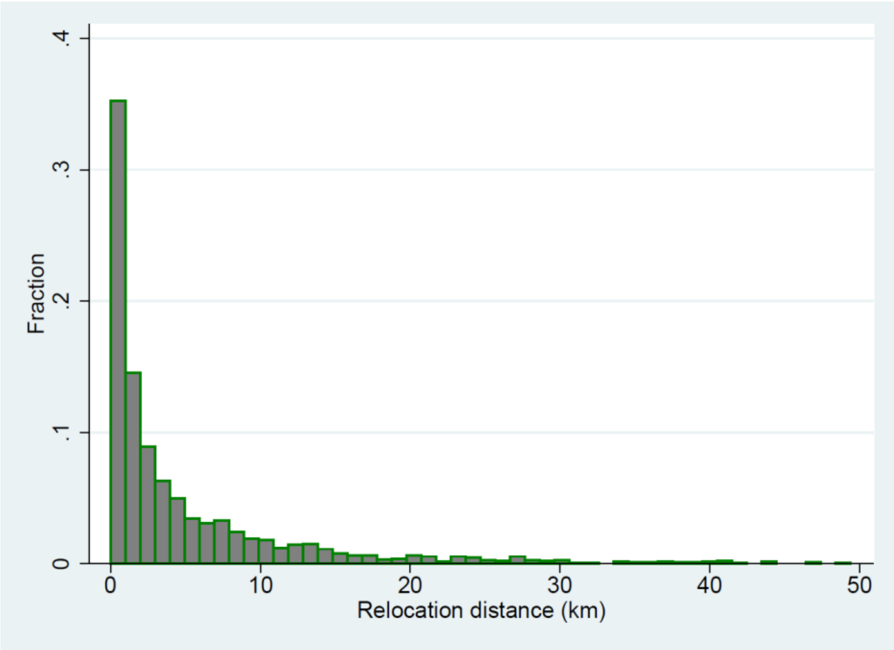

Figure 2: Distribution of relocated firms by distance of relocation

Figure 2 shows the distribution of firm relocation distance in the sample. The distribution is skewed to the right since most relocated firms in the sample moved within a short distance from their initial location. The average relocation distance for relocated firms is about 7 km while its median is 2 km. About 83 percent of relocations took place within 10 km distance; 98 percent within 50 km; and only 12 firms relocated more than 100 km away.

2.2 Worker turnover

Worker turnover measures the number of workers separating from their firm during a particular period. Often, it is calculated as a proportion of workers leaving a firm in a given year out of the total number of workers who were with the firm in that year. For the purpose of this paper, however, we define worker turnover rates based on the number of workers at a firm at the beginning of a base year, the year in which we observe a firm's relocation status. This is done to distinguish workers who were with the firm before its relocation from new workers who are recruited after the relocation, as the latter are unaffected by the relocation. We refer to the base year as year 0 and subsequent years as year 1, year 2 and year 3, consecutively.

To formally define worker turnover rate as used in this paper, let N_t be the number of workers that a firm has at the beginning of a base year, t, and $L_{t,s}$ be the number of workers who were with the firm since the beginning of the base year and subsequently exited in the year $t+s$, where $s = 0, 1, 2, 3$. Then, we calculate the rate of worker turnover as

$$r_s = \begin{cases} \frac{L_{t,0}}{N_t} & \text{for } s = 0, \\ \frac{L_{t,s}}{N_t - \sum_s L_{t,s-1}} & \text{for } s = 1, 2, 3 \end{cases} \tag{1}$$

One can obtain the survival rate by subtracting the rate of worker turnover from one.[4] In other words, the rate of worker turnover equals one less the proportion of stayers out of those who were with the firm since the base year and stayed until the previous year. This notion of worker turnover has two important features: (a) it distinguishes workers who were with the firm before (a potential) relocation from new workers recruited after the relocation; (b) it focuses only on workers who have stayed with the firm from the base year until the beginning of the respective year, neglecting those who left the firm in between.

There are various reasons why workers separate from their employers, including voluntary quits initiated by workers, retirements, death, disability, layoffs and closing down of a firm. Ideally, we wish to model the extent to which relocation distance affects voluntary job moves. Unfortunately, however, we do not distinguish reasons for separation in the dataset. As a result, our definition of worker turnover can also include involuntary layoffs, deaths and disability. Nevertheless, it does not include separations due to closing firms as we considered continuing establishments alone.

3 Data and descriptive statistics

3.1 The data

The analysis is based on Danish register data obtained from Statistics Denmark. The data contains information about all workers and all firms in the country. We used a

[4]The rate of survival rate measures the proportion of workers who stays with their firm.

Table 1: Firms across years and by relocation status

Year	Number of firms	Relocated firms	
		Frequency	Share from total
2001	11,961	237	1.98
2002	12,933	296	2.29
2003	12,799	274	2.14
2004	12,756	277	2.17
2005	12,797	153	1.20
2006	12,881	302	2.34
2007	11,877	273	2.30

matched employee-employer data for the years 2000–2007. We exclude small firms, those with less than 10 workers in each one of the years in the sample, for different reasons. Firstly, factors that induce relocation and turnover decisions in small, and often self- and family-owned establishments tend to differ from factors that influence these decisions in larger firms. If these factors are not observed in the data, they can cause bias. Secondly, as individual workers can highly influence relocation decisions in small firms, a change in workplace location could be self-motivated, and hence it may not induce behavioural response in terms of job mobility. As Mulalic *et al.* (2013) argued, however, relocation decisions in large firms can be considered exogenous from the perspective of individual workers. Moreover, although all employers could contemplate the effect of relocation on their workers, small firms could have higher tendency to do so, and this induce serious bias in estimation.

By construction, firms that are not observed in the dataset at least for two consecutive years are excluded from the analysis. Although most relocated firms did relocate only once during the sample period, some (about 10 percent of relocated firms) relocated several times during the period under consideration. For firms that relocated multiple times during the sample period, the outcome of interest is subject to multiple shocks hence it is difficult to attribute the effect to one of the relocations. Therefore, we do not include them in the analysis. Although we have no justification, it shall be commented that, for year 2005, a share of relocated firms is relatively lower.

The total number of unique firms in our sample is 14,923; and this figure fluctuates between 11,877 and 12,933 in a given year (see Table 1). Overall, about 12 percent of firms had relocated during the sample period. The share of relocated firms varies between 1.20% and 2.34% of the total number of firms in any given year in the sample.

3.2 Worker turnover rates

Although there is some variation in the average rate of worker turnover over time, the difference is generally very small (see Table 8 in the Appendix). On average, about 21% of workers in a non-relocated firm have left during a given year. This figure ranges from about 20 to 25% in any given year in the sample. For firms relocated within 3 km (21.6%) or more than 3 km away (23.2%), the average rate of worker turnover is higher (see Table 9 in the Appendix for a summary statistics of the rate of worker turnover). Interestingly, we do not find significant difference in the average rate of worker turnover between non-relocated firms and firms relocated within short distance (3 km).[5] This indicates that relocation distance is not subsuming the effect of restructuring of the firm following relocation. Generally, relocated firms have pre-relocation characteristics that are largely similar to non-relocated firms.

Survival rates decline over time irrespective of a firm's relocation status, *i.e.*, a declining share of workers who stayed since a base year (year 0) had eventually left the firm. Out of all workers with a firm at the start of a base year, about 21% left in the same year, while 14%, 10.6% and 8.6% left in the following three years, consecutively. In other words, a typical firm loses 35% of its workers in two years, 45.7% in three years and 54.2% in four years. This suggests a negative relationship between job tenure and job mobility decisions; in line with a previous finding by Eriksson & Westergaard-Nielsen (2009). Overall, non-relocated firms and those that relocated within a short distance experience a lower rate of worker turnover than firms that relocated more than 3 km away (see Table 2).

The average survival and turnover rates also exhibit a similar pattern over a coarser category of relocation distance (see Table 2). The cumulative survival rate declined over time as more and more workers moved jobs. On average, the cumulative survival rate is

[5] A t-test for the equality of the two means is rejected. Besides the t-test, we also apply propensity score matching method (by matching the two groups based on pre-relocation characteristics) and find no significant difference.

Table 2: Average worker turnover and survival rates by relocation status and distance

	Worker turnover rate				Cumulative survival rate			
	Year 0	Year 1	Year 2	Year 3	Year 0	Year 1	Year 2	Year 3
Non-relocated firms	0.209	0.181	0.166	0.157	0.791	0.65	0.544	0.459
Relocated firms where relocation distance is								
less than 1km	0.219	0.199	0.172	0.172	0.781	0.629	0.520	0.431
between 1 – 5 km	0.216	0.193	0.184	0.161	0.784	0.635	0.520	0.434
between 5 – 10 km	0.229	0.200	0.173	0.173	0.771	0.624	0.518	0.424
between 10 – 20 km	0.226	0.236	0.205	0.163	0.774	0.597	0.479	0.404
between 20 – 50 km	0.244	0.224	0.163	0.172	0.756	0.596	0.496	0.408
over 50 km	0.281	0.320	0.303	0.273	0.719	0.500	0.353	0.231
Overall	0.210	0.181	0.166	0.157	0.790	0.650	0.543	0.458

higher for non-relocated firms and firms relocated within a shorter distance than those that relocated farther way. For instance, after four years, firms that had relocated over 50 km kept only 23% of their workers in the base year compared to the 41% for firms relocated between 20-50 km and 46% for non-relocated firms.

Table 3: Average pre-relocation characteristics of workers who stayed at relocated firms

	Pre-relocation	Year 0	Year 1	Year 2	Year 3
Average commuting (km)	18.53	17.80	18.80	17.94	17.92
Average experience (years)	18.84	20.22	20.97	21.70	22.44
Share completing higher education (%)	33.30	33.40	33.20	33.10	32.60
Share having children (%)	20.90	18.20	17.90	17.20	15.80
Share of male workers (%)	54.80	55.30	55.50	55.30	56.00

To investigate whether workers who leave differ from those who stay, we compare the characteristics of workers in relocated firms prior to relocation against the pre-relocation characteristics of workers who stayed after relocation. This is shown in Table 3. The average commuting distance of stayers has declined, albeit non-smoothly, as more and more long distance commuters left after relocation. In contrast, the average experience of stayers has increased as a higher share of more experienced workers stayed after relocation. Moreover, fewer female workers and those having children have stayed after the relocation. In general, there seems to be some systematic difference between workers who stay and those who leave in the aftermath of firm relocation.

4 Estimation results and discussion

4.1 Estimation

Let $d_{i,t} \geq 0$ be firm i's relocation distance in a base year t such that $d_{i,t} > 0$ if firm i had relocated or zero otherwise. We model the rate of worker turnover with the following general linear model:

$$r_{i,s} = \alpha_s + \beta_s d_{i,t} + \boldsymbol{\theta}_s' \boldsymbol{x}_{i,t} + \varepsilon_{i,s} \tag{2}$$

where $\boldsymbol{x}$ is a vector of firm-level base year characteristics; ε is the error term; α, β, and $\boldsymbol{\theta}$ are parameters of the model. Since the response variable is continuous, one can estimate the model in (2) using Ordinary Least Squares (OLS) method. The set of additional covariates, $\boldsymbol{x}_{i,t}$, includes the number of workers as a measure of firm size; average experience of workers and share of workers with higher education as a measure of skill intensity, the industry in which the firm operates, the average commuting distance of workers, the share of male workers and those having children. The level of most of these variables represent the values of the respective variable at the beginning of a base year, i.e., before the firm's potential relocation.

We estimate the model on a combined sample of relocated and non-relocated firms by including a dummy indicator for firm relocation. This way we can examine if firm relocation has an effect on its own after controlling for the distance of relocation. Besides other covariates, the model also includes year dummies to account for the effect of general economic performance and labour market conditions on worker turnover. This is so since more workers voluntary leave their jobs during boom or in periods of low unemployment (Frederiksen & Westergaard-Nielsen, 2007; Eriksson & Westergaard-Nielsen, 2009). The model also includes workplace municipality dummies to account for differences across regions such as the size and feature of local labour and product markets. Moreover, since firms in the same municipality share various common characteristics, they may tend to experience similar rates of worker turnover. We account for the effect of this on standard errors by clustering them by municipality. We have also included industry dummies.

4.2 Results from the OLS model

Estimation results from an ordinary least square model are summarised in Table 4. The first column contains results from a model in which the response variable is worker turnover rate in the base year (year 0). The next three columns display estimation results in a model where the response variable is the rate of worker turnover in successive years after the base year. In general, estimates show that the rate of worker turnover is higher at longer distance of relocation. The estimate of relocation distance is statistically significant except in year 3. The effect of relocation distance is smaller in the base year. It becomes stronger in the next two years after which, it faded away and becomes insignificant.

The estimated effect for the base year shows that a 10 km increase in a firm's relocation distance, on average, increases the rate of worker turnover by 0.4 percentage points, which represents 2% of the average annual rate of worker turnover for non-relocated firms, or alternatively a 0.5% reduction in survival rate. The effect of relocation distance in the base year, as well as in subsequent years, depends on the amount of time workers require to adjust to the change in workplace location. The adjustment period, in turn, depends on whether workers knew about relocation decisions ahead of the actual relocation, availability of alternative jobs, and the cost of job search and residence moves. Bearing in mind that some firms could have relocated later in the base year such that workers in these firms have had relatively short time to conform to the change, the estimated effect of relocation distance in the base year could suggest prior knowledge of relocation decisions and/or easier access to other jobs. To the extent that workers learn about the relocation at the time when it occurs, the estimated effect in the base year is likely to be understated.

As expected, the effect of relocation distance is stronger in year 1; it is over double the effect in the base year. The estimate suggests that a 10 km increase in relocation distance increases the exit rate of workers who stayed in the base year by 1.1%. In terms of the number of workers prior to relocation, this translates to an increase in worker turnover by 0.9 percentage points.[6] The relatively stronger effect in this year is not surprising since, with longer search period, more and more workers will be able to find and move to other jobs. The coefficient estimate of relocation distance in year 2 is significant and

[6]This is found by multiplying the coefficient estimate in year 1 by the average proportion of workers who did not move jobs during the base year.

Table 4: Estimation results from a standard regression model

	Dependent variable is the rate of worker turnover in:			
	Year 0	Year 1	Year 2	Year 3
Relocation distance (km)	0.00043**	0.00114***	0.00105*	0.00046
	(0.00021)	(0.00041)	(0.00059)	(0.00033)
Relocation indicator (=1 if relocated)	-0.00155	0.00575	0.00458	0.00242
	(0.00334)	(0.00379)	(0.00558)	(0.00455)
Number of workers	0.00001	0.00003***	0.00003***	0.00004***
	(0.00001)	(0.00001)	(0.00001)	(0.00001)
Average experience of workers (years)	-0.01525***	-0.01243***	-0.01071***	-0.00887***
	(0.00059)	(0.00060)	(0.00059)	(0.00061)
Share of workers having children	-0.01585***	-0.03194***	-0.04328***	-0.05392***
	(0.00610)	(0.00641)	(0.00629)	(0.00733)
Average commute of workers (km)	0.00106***	0.00073***	0.00057***	0.00054***
	(0.00009)	(0.00010)	(0.00008)	(0.00009)
Share of workers with higher education	-0.06118***	-0.05214***	-0.04849***	-0.04605***
	(0.00215)	(0.00200)	(0.00197)	(0.00232)
Manufacturing or construction sector	0.03130***	0.02463***	0.01691***	0.01189***
	(0.00255)	(0.00207)	(0.00216)	(0.00254)
Change in total employment	-0.00107***	-0.00013***	-0.00008**	-0.00010***
	(0.00022)	(0.00004)	(0.00004)	(0.00003)
Share of male workers	-0.04707***	-0.03285***	-0.02921***	-0.03222***
	(0.00380)	(0.00400)	(0.00370)	(0.00455)
Constant	0.50265***	0.40313***	0.37700***	0.70395***
	(0.01163)	(0.01064)	(0.00993)	(0.01113)
Observations	86,877	71,870	57,760	44,503
R-squared	0.17	0.09	0.071	0.058

In parenthesis are std. errors clustered by municipality. ***, ** and * denote statistical significance at the 1%, 5% and 10% levels, respectively. Each model includes year and municipality fixed effects.

comparable to that in year 1. In year 3, the estimated effect does not only fade away but also it becomes insignificant. This suggest that workers have adjusted to the relocation in the first three years.

Is the cumulative effect in two or three years significant? We compute the standard error of the cumulative effect in two and in three years assuming rates of worker turnover are independent. This is a rather a strong assumption made only to provide a picture of the cumulative effect. The standard error of the sum of the coefficients turns out to be 0.00046 in the first two years, and 0.00075 in the first three years. In each case, the sum of the coefficients is more than double the respective standard error indicating that the cumulative effects is statistically significant.

Although significant and positive as expected, the estimated effect of relocation distance on worker turnover is rather moderate considering the average commuting distance of employed individuals in Denmark.[7] It is not surprising that we obtained a lower effect since (a) the high rate of job mobility in Denmark means that workers expect to be mobile in the labour market; hence, it may matter less when their firm relocates; (b) if workers knew about the relocation earlier and moved before it took place, the effect would not be captured in our analysis.

However, the estimated effect can also be underestimated due to several reasons: First, random error in our measure of relocation distance can attenuate the estimated effect. This is likely to be the case since our measure of relocation distance is not accurate. Second, if relocation induced many workers to leave such that less than 10 stayed subsequently, then this firm is not included in the analysis since we considered firms that have at least 10 workers in any given year in the sample. To the extent that this was the case, the estimated effect represents a lower bound. Thirdly, since employers can contemplate the effect of relocation on their workers, they may not move to the extent that they would lose their best employees. This self-selection can partly explain the small estimated effect. Moreover, wages are likely to be correlated with both relocation distance (since firms may offer compensation for commuting) and worker turnover (as higher wages induce tenure). However, we do not control for wage in our model. Hence, it possible that we have obtained a lower estimate than if we had controlled for wages.

Interestingly, the coefficient estimates associated with the relocation indicator are not significant suggesting that, conditional on covariates in the model, both relocated and non-relocated firms have experienced comparable worker turnover. It indicates that relocation distance is not subsuming the effect of the spatial relocation per se. Moreover, results from a model estimated based on a sample of firms relocated within 3 km distance (see Table 10 in Appendix) show that the coefficient estimate of relocation distance has become negative and often insignificant. This indicates that, for firms that move within short distance, relocation distance does not significantly explain worker turnover rates.

Besides relocation distance and a dummy indicating relocation, the model also include firm size to examine if larger firms can maintain lower worker turnover due to their capacity to pay competitive wages. Although the coefficient estimate of firm size (number

[7]Figures from Statistics Denmark indicate that more than 90% of employed individuals in the country commute less than 50 km one way; and more than a third of these individuals commute less than 10 km one way.

of workers) turned out to be positive, contradicting past evidence (e.g. Idson, 1993), the estimate is negligible in magnitude. Another control variable in the model is the average commuting distance of workers at a firm. The estimate of this variable is significant and positive indicating that, on average, firms that are located farther from their employees face higher worker turnover. Interestingly, this coefficient is in the same order of magnitude as the respective coefficient of relocation distance indicating that firms located farther away from their workers have experienced higher rate of worker turnover.

Results also suggest that firms that had more experienced workers faced lower worker turnover. This result can indicate a better worker-firm match prior to relocation. More experienced workers may seek to remain at their current job as they may have settled after several job moves early in their career. Alternatively, the estimate can suggest that a firm pays higher wages to senior workers to prevent them from leaving. Results also show that, a firm that has a higher proportion of its workers as parents experienced lower worker turnover. This result could indicate restrictions parents face in moving residences (Munch *et al.* , 2008).

Worker turnover could vary across industries. Workers in certain sectors are educated and trained to have easily transferable skills, which enhances worker turnover. This is specially the case in manufacturing and construction industries. Our estimates support this indicating that, compared to firms in other industries, those in manufacturing and construction industries experienced significantly higher rates of worker turnover.

Firms with a higher percentage of highly educated workers can have higher or lower turnover. While workers with higher education can perform tasks requiring lower skills, they may however have limited alternative employers in their specialised skill and may be more reluctant to accept other jobs that are less favourable. We included as controls the percentage of workers completing short, medium and long-cycle higher education and those with bachelor and PhD degrees. The associated coefficient is negative and significant.

Involuntary separations are more likely to be the case if a firm is downsizing than otherwise. One can account for downsizing by including in the model the number of workers at a firm in subsequent years. However, the number of workers in the base year is highly correlated with the number of workers in subsequent years. Instead, we include the change in total employment, the difference in the number of workers at a firm in the current year and that in the previous year. The associated coefficient estimate is, as expected, significant suggesting that the survival rate is lower if a firm is downsizing than otherwise. By doing this, we isolate the effect of relocation associated with up- or downscaling from that induced by the relocation distance thereof.

4.3 Results from a fractional logit model

The dependent variable in our analysis is a proportion measuring the fraction of workers separating from their firm from one (base) year to subsequent years. Therefore, it only assumes values between zero and one inclusive. Though one can use an OLS method to model the fraction of separations, as we did above, this method does not recognize the bounded nature of the response variable. As a result, there is no guarantee that the predicted worker turnover rates fall within the zero-one bound. A Tobit model would be a better option since it acknowledges the zero lower bound. Nevertheless, as Papke & Wooldridge (1996) argued, the Tobit model might not be applicable where values below the censoring point, in our case zero, are infeasible.

The fractional logit model proposed by Papke & Wooldridge (1996) is more suited for this particular purpose. The model is estimated using a Generalised Linear Model (GLM), in which the conditional mean is assumed to follow a logistic distribution. The model in (1) is estimated using a fractional logit model, and Table 5 shows the average marginal effects from this model. Overall, the average partial effects from this model are comparable to the corresponding marginal effects from the standard linear regression model. For the target variable, the average marginal effects from the fractional logit model are 24-39% lower than the corresponding marginal affects under OLS. The pattern of estimated effects is also similar: the effect is strongest in year 1 and year 2, and it declines and become insignificant in year 3.

Estimated marginal effects of the remaining covariates in this model are, in most cases, similar to the corresponding marginal effects from the linear model. A noticeable exception is the coefficient estimate of the relocation indicator in year 1: contrary to the linear model, the estimate in this model is statistically significant. In general, however, results are largely similar under the two models; thus, we continue to use OLS estimates for ease

Table 5: Average partial effects from a fractional logit model

	Dependent variable is the rate of worker turnover in:			
	Year 0	Year 1	Year 2	Year 3
Relocation distance (km)	0.00026*	0.00083***	0.00076**	0.00035
	(0.00015)	(0.00029)	(0.00038)	(0.00026)
Relocation indicator (=1 if relocated)	-0.00079	0.00672***	0.00573	0.00282
	(0.00302)	(0.00332)	(0.00497)	(0.00424)
Number of workers	-0.00003***	0.00002***	0.00003***	0.00003***
	(0.00001)	(0.000001)	(0.00001)	(0.000001)
Average experience of workers (years)	-0.01448***	-0.01170***	-0.01008***	-0.00841***
	(0.00046)	(0.00044)	(0.00046)	(0.00049)
Share of workers having children	-0.00669	-0.02502***	-0.03753***	-0.04982***
	(0.00593)	(0.00677)	(0.00661)	(0.00737)
Average commute of workers (km)	0.00096***	0.00070***	0.00056***	0.00053***
	(0.00009)	(0.00010)	(0.00008)	(0.00008)
Share of workers with higher education	-0.06145***	-0.05473***	-0.05078***	-0.04801***
	(0.00185)	(0.00204)	(0.00194)	(0.00233)
Manufacturing or construction sector	0.03026***	0.02454***	0.01731***	0.01271***
	(0.00220)	(0.00194)	(0.00204)	(0.00253)
Change in total employment	-0.00206***	-0.00010***	-0.00006***	-0.00007***
	(0.00024)	(0.00005)	(0.00003)	(0.00002)
Share of male workers	-0.04714***	-0.03337**	-0.02960***	-0.03250***
	(0.00339)	(0.00391)	(0.00360)	(0.00452)
Observations	86877	71870	57760	44503

In parenthesis are std. errors clustered by municipality. ***, ** and * denote statistical significance at the 1%, 5% and 10% levels, respectively. Each model includes year and municipality fixed effects.

of interpretation.

5 Sensitivity analysis

In this section, we examine how much results in the previous section depend on some issues that can potentially affect the estimated effect. This includes probing the effect of outlier information about changes in commuting distance on our results; and examining if results vary by selection of the sample based on firm size.

Robustness of the measure of relocation distance

Since we compute relocation distance based on the largest absolute change in the commuting distance for workers who did not move job and residence, it can be sensitive to outlier information on changes in commutes. That is, relocation distance can change if we exclude one or more workers who stayed with the firm and experienced largest changes in commuting distance. To examine how much this affects our results, we estimate the model by excluding some workers who did not move job and residence and faced the largest absolute change in commuting distance. Table 6 shows coefficient estimates for the target variable; detailed estimation results are given in Table 11 through to Table 15 in the Appendix.

Table 6: The coefficient of relocation distance computed after excluding some workers who did not change job and residence, and faced largest changes in commuting distance

Relocation distance calculated after excluding commutes of workers who did not move job & residence and faced the:	Estimate of β where the dependent variable is worker turnover rate in:			
	Year 0	Year 1	Year 2	Year 3
– largest change in commuting distance	0.00036	0.00146***	0.00114	0.00031
	(0.00022)	(0.00050)	(0.00071)	(0.00035)
– two largest changes in commuting distance	0.00034	0.00152***	0.00122*	0.00033
	(0.00024)	(0.00051)	(0.00073)	(0.00037)
– three largest changes in commuting distance	0.00034	0.00153***	0.00127*	0.00034
	(0.00025)	(0.00052)	(0.00075)	(0.00038)
– four largest changes in commuting distance	0.00035	0.00154***	0.00130*	0.00035
	(0.00025)	(0.00053)	(0.00076)	(0.00039)
– five largest changes in commuting distance	0.00035	0.00155***	0.00133*	0.00037
	(0.00025)	(0.00054)	(0.00077)	(0.00040)

In parenthesis are std. errors clustered by municipality. ***, ** and * denote statistical significance at the 1%, 5% and 10% levels, respectively. Each model includes year and municipality fixed effects.

Estimates and their standard errors remained largely comparable indicating the robustness of our results to outlier information on the measure of relocation distance. This is not surprising since relocation distance hardly changes despite the exclusion of largest changes in commuting distance of workers who did not move job and residences. In contrast to results in the previous section, the estimated effect in the base year is significant only at the 15% level and about 16% lower.

Do our results vary if the sample only involves firms with more workers?

Our analysis so far is based on a sample of firms with at least 10 workers in each year in the sample period. We also examine whether our results change if we estimate the model based on a sample of larger firms. Estimation results from a model based on a subsample of firms with at least 15 and 30 workers in a given year in the sample is shown in Table 7 (detailed estimation results are shown in Table 16 and Table 17 in the Appendix). Despite some dissimilarity in the size of estimates and their standard errors, results are generally comparable. The cumulative effect over three years is the same as before. A surprising result is the negative coefficient estimate in year 2 for a subsample of firms with at least 30 workers in a given year. This coefficient is however only marginally significant.

Table 7: Firms with at least 15 or 30 workers in any given year in the sample

	Estimate of β where the dependent variable is worker turnover rate in:			
	Year 0	Year 1	Year 2	Year 3
Firms with 15 or more workers in a given year	0.00041*	0.00108***	0.00040	0.00069**
	(0.00021)	(0.00037)	(0.00046)	(0.00035)
Firms with 30 or more workers in a given year	0.00060	0.00151***	-0.00042*	0.00057
	(0.00041)	(0.00055)	(0.00021)	(0.00043)

In parenthesis are std. errors clustered by municipality. ***, ** and * denote statistical significance at the 1%, 5% and 10% levels, respectively. Each model includes the full set of covariates and year and municipality fixed effects.

6 Conclusion

Using Danish register data for the year 2000-2007, this study investigates the extent to which the relocation distance of moving firms affects worker turnover at the firm level. The empirical results in the paper show that relocation distance has a moderate but significant effect on worker turnover: e.g., a 10 km increase in relocation distance increases the average annual rate of worker turnover at the firm level by 2-4 percent in three years, including the year of relocation. The effect is smaller in the year of relocation; and becomes relatively stronger in the next two years before it eventually fades away as workers adjust to the change. The implication of these results is that, if or when employers decide to change workplace location, they ought to contemplate the effect of the relocation distance on the commutes of their workers and the resultant loss in human power. The findings in this study corroborate results in previous research (e.g. Zax & Kain, 1996; Levinson, 1997; van Ommeren *et al.* , 1999) that establish a link between commuting distance and job moving behaviour.

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Appendix

Table 8: Average worker turnover rates by year and distance of relocation

		Year							Overall
		2001	2002	2003	2004	2005	2006	2007	
Year 0	Non-relocated	0.199	0.205	0.202	0.2	0.197	0.217	0.249	0.209
	Relocated within 3 km	0.194	0.215	0.205	0.208	0.198	0.224	0.254	0.216
	Relocated over 3 km	0.245	0.222	0.238	0.2	0.205	0.241	0.259	0.232
Year 1	Non-relocated	0.135	0.131	0.132	0.131	0.147	0.168		0.14
	Relocated within 3 km	0.145	0.133	0.138	0.146	0.165	0.176		0.15
	Relocated over 3 km	0.137	0.156	0.154	0.162	0.183	0.185		0.161
Year 2	Non-relocated	0.153	0.152	0.152	0.171	0.201			0.166
	Relocated within 3 km	0.142	0.181	0.16	0.178	0.215			0.173
	Relocated over 3 km	0.169	0.182	0.189	0.212	0.245			0.193
Year 3	Non-relocated	0.14	0.141	0.159	0.19				0.157
	Relocated within 3 km	0.132	0.153	0.15	0.21				0.163
	Relocated over 3 km	0.161	0.175	0.173	0.207				0.179

Table 9: Summary of the rate of worker turnover by distance of relocation

		Observations	Minimum	Median	Mean	Std deviation	Maximum
Year 0	Non-relocated	86,172	0	0.188	0.209	0.130	1.000
	Relocated < 3 km	1,052	0	0.196	0.216	0.139	1.000
	Relocated ≥ 3 km	760	0	0.214	0.232	0.132	0.778
Year 1	Non-relocated	71,348	0	0.158	0.181	0.128	1.000
	Relocated < 3 km	887	0	0.171	0.194	0.133	0.800
	Relocated ≥ 3 km	649	0	0.188	0.219	0.156	1.000
Year 2	Non-relocated	57,559	0	0.143	0.166	0.130	1.000
	Relocated < 3 km	679	0	0.147	0.173	0.138	1.000
	Relocated ≥ 3 km	464	0	0.154	0.193	0.169	1.000
Year 3	Non-relocated	44,406	0	0.133	0.157	0.135	1.000
	Relocated < 3 km	548	0	0.133	0.163	0.143	0.886
	Relocated ≥ 3 km	389	0	0.154	0.178	0.140	0.850

Table 10: Estimates based of a sample of firms with relocation distance < 3 km

	Dependent variable is the rate of worker turnover in:			
	Year 0	Year 1	Year 2	Year 3
Relocation distance (km)	-0.00762	-0.00614	-0.00377	-0.01435*
	(0.00619)	(0.00447)	(0.00564)	(0.00793)
Relocation indicator (=1 if relocated)	0.00702	0.01406***	0.00821	0.01389
	(0.00799)	(0.00513)	(0.00829)	(0.00989)
Number of workers	0.00001	0.00003***	0.00003***	0.00004***
	(0.00001)	(0.00001)	(0.00001)	(0.00001)
Average experience of workers (years)	-0.01526***	-0.01240***	-0.01068***	-0.00892***
	(0.00059)	(0.00060)	(0.00056)	(0.00059)
Share of workers having children	-0.01562**	-0.03072***	-0.04166***	-0.05451***
	(0.00607)	(0.00638)	(0.00643)	(0.00735)
Average commute of workers (km)	0.00107***	0.00073***	0.00057***	0.00054***
	(0.00010)	(0.00011)	(0.00008)	(0.00009)
Share of workers with higher education	-0.06109***	-0.05214***	-0.04851***	-0.04655***
	(0.00215)	(0.00198)	(0.00195)	(0.00233)
Manufacturing or construction sector	0.03120***	0.02456***	0.01670***	0.01187***
	(0.00256)	(0.00203)	(0.00215)	(0.00249)
Change in total employment	-0.00108***	-0.00013***	-0.00009***	-0.00010***
	(0.00022)	(0.00004)	(0.00003)	(0.00003)
Share of male workers	-0.04712***	-0.03289***	-0.02926***	-0.03249***
	(0.00383)	(0.00398)	(0.00365)	(0.00458)
Constant	0.46866***	0.36622***	0.35318***	0.70528***
	(0.01247)	(0.01195)	(0.00996)	(0.01084)
Observations	86,128	71,230	57,303	44,119
R-squared	0.170	0.089	0.071	0.058

In parenthesis are std. errors clustered by municipality. ***, ** and * denote statistical significance at the 1%, 5% and 10% levels, respectively. Each model includes year and municipality fixed effects.

Table 11: Estimates after excluding the largest absolute change in commuting distance

	Dependent variable is the rate of worker turnover in:			
	Year 0	Year 1	Year 2	Year 3
Relocation distance (km)	0.00036	0.00146***	0.00114	0.00031
	(0.00022)	(0.00050)	(0.00071)	(0.00035)
Relocation indicator (=1 if relocated)	-0.00062	0.00543	0.00567	0.00397
	(0.00323)	(0.00367)	(0.00542)	(0.00442)
Number of workers	0.00001	0.00003***	0.00003***	0.00004***
	(0.00001)	(0.00000)	(0.00001)	(0.00001)
Average experience of workers (years)	-0.01525***	-0.01243***	-0.01071***	-0.00887***
	(0.00059)	(0.00060)	(0.00059)	(0.00061)
Share of workers having children	-0.01586***	-0.03196***	-0.04330***	-0.05391***
	(0.00610)	(0.00642)	(0.00629)	(0.00733)
Average commute of workers (km)	0.00106***	0.00073***	0.00057***	0.00054***
	(0.00009)	(0.00010)	(0.00008)	(0.00009)
Share of workers with higher education	-0.06118***	-0.05212***	-0.04846***	-0.04603***
	(0.00215)	(0.00200)	(0.00196)	(0.00232)
Manufacturing or construction sector	0.03131***	0.02459***	0.01690***	0.01188***
	(0.00255)	(0.00207)	(0.00216)	(0.00255)
Change in total employment	-0.00107***	-0.00012***	-0.00008*	-0.00010***
	(0.00022)	(0.00004)	(0.00004)	(0.00003)
Share of male workers	-0.04706***	-0.03282***	-0.02918***	-0.03222***
	(0.00380)	(0.00400)	(0.00371)	(0.00456)
Constant	0.50316***	0.40163***	0.37746***	0.70385***
	(0.01162)	(0.01060)	(0.00991)	(0.01114)
Observations	86,877	71,870	57,760	44,503
R-squared	0.170	0.090	0.071	0.058

In parenthesis are std. errors clustered by municipality. ***, ** and * denote statistical significance at the 1%, 5% and 10% levels, respectively. Each model includes year and municipality fixed effects.

Table 12: Estimates after excluding 2 largest absolute changes in commuting distance

	Dependent variable is the rate of worker turnover in:			
	Year 0	Year 1	Year 2	Year 3
Relocation distance (km)	0.00034	0.00152***	0.00122*	0.00033
	(0.00024)	(0.00051)	(0.00073)	(0.00037)
Relocation indicator (=1 if relocated)	-0.00040	0.00552	0.00552	0.00393
	(0.00325)	(0.00366)	(0.00537)	(0.00442)
Number of workers	0.00001	0.00003***	0.00003***	0.00004***
	(0.00001)	(0.000001)	(0.00001)	(0.00001)
Average experience of workers (years)	-0.01525***	-0.01243***	-0.01071***	-0.00887***
	(0.00059)	(0.00060)	(0.00059)	(0.00061)
Share of workers having children	-0.01586***	-0.03194***	-0.04330***	-0.05391***
	(0.00610)	(0.00642)	(0.00629)	(0.00733)
Average commute of workers (km)	0.00106***	0.00073***	0.00057***	0.00054***
	(0.00009)	(0.00010)	(0.00008)	(0.00009)
Share of workers with higher education	-0.06118***	-0.05212***	-0.04846***	-0.04603***
	(0.00215)	(0.00200)	(0.00196)	(0.00232)
Manufacturing or construction sector	0.03131***	0.02460***	0.01691***	0.01189***
	(0.00255)	(0.00207)	(0.00216)	(0.00255)
Change in total employment	-0.00107***	-0.00012***	-0.00008*	-0.00010***
	(0.00022)	(0.00004)	(0.00004)	(0.00003)
Share of male workers	-0.04707***	-0.03282***	-0.02918***	-0.03222***
	(0.00380)	(0.00400)	(0.00371)	(0.00456)
Constant	0.50313***	0.40361***	0.37750***	0.70385***
	(0.01162)	(0.01069)	(0.00990)	(0.01114)
Observations	86,877	71,870	57,760	44,503
R-squared	0.17	0.09	0.071	0.058

In parenthesis are std. errors clustered by municipality. ***, ** and * denote statistical significance at the 1%, 5% and 10% levels, respectively. Each model includes year and municipality fixed effects.

Table 13: Estimates after excluding 3 largest absolute changes in commuting distance

	Dependent variable is the rate of worker turnover in:			
	Year 0	Year 1	Year 2	Year 3
Relocation distance (km)	0.00034	0.00153***	0.00127*	0.00034
	(0.00025)	(0.00052)	(0.00075)	(0.00038)
Relocation indicator (=1 if relocated)	-0.00035	0.00570	0.00548	0.00396
	(0.00325)	(0.00367)	(0.00536)	(0.00441)
Number of workers	0.00001	0.00003***	0.00003***	0.00004***
	(0.00001)	(0.00000)	(0.00001)	(0.00001)
Average experience of workers (years)	-0.01525***	-0.01243***	-0.01071***	-0.00887***
	(0.00059)	(0.00060)	(0.00059)	(0.00061)
Share of workers having children	-0.01586***	-0.03193***	-0.04329***	-0.05390***
	(0.00610)	(0.00642)	(0.00629)	(0.00733)
Average commute of workers (km)	0.00106***	0.00073***	0.00057***	0.00054***
	(0.00009)	(0.00010)	(0.00008)	(0.00009)
Share of workers with higher education	-0.06118***	-0.05212***	-0.04846***	-0.04603***
	(0.00215)	(0.00200)	(0.00196)	(0.00232)
Manufacturing or construction sector	0.03131***	0.02461***	0.01691***	0.01189***
	(0.00255)	(0.00207)	(0.00216)	(0.00255)
Change in total employment	-0.00107***	-0.00012***	-0.00008*	-0.00010***
	(0.00022)	(0.00004)	(0.00004)	(0.00003)
Share of male workers	-0.04707***	-0.03282***	-0.02918***	-0.03222***
	(0.00380)	(0.00400)	(0.00371)	(0.00456)
Constant	0.50312***	0.40086***	0.37736***	0.70385***
	(0.01162)	(0.01058)	(0.00990)	(0.01114)
Observations	86,877	71,870	57,760	44,503
R-squared	0.17	0.09	0.071	0.058

In parenthesis are std. errors clustered by municipality. ***, ** and * denote statistical significance at the 1%, 5% and 10% levels, respectively. Each model includes year and municipality fixed effects.

Table 14: Estimates after excluding 4 largest absolute changes in commuting distance

	Dependent variable is the rate of worker turnover in:			
	Year 0	Year 1	Year 2	Year 3
Relocation distance (km)	0.00035	0.00154***	0.00130*	0.00035
	(0.00025)	(0.00053)	(0.00076)	(0.00039)
Relocation indicator (=1 if relocated)	-0.00034	0.00591	0.00552	0.00393
	(0.00324)	(0.00365)	(0.00532)	(0.00440)
Number of workers	0.00001	0.00003***	0.00003***	0.00004***
	(0.00001)	(0.00000)	(0.00001)	(0.00001)
Average experience of workers (years)	-0.01525***	-0.01243***	-0.01071***	-0.00887***
	(0.00059)	(0.00060)	(0.00059)	(0.00061)
Share of workers having children	-0.01586***	-0.03193***	-0.04330***	-0.05390***
	(0.00610)	(0.00642)	(0.00629)	(0.00733)
Average commute of workers (km)	0.00106***	0.00073***	0.00057***	0.00054***
	(0.00009)	(0.00010)	(0.00008)	(0.00009)
Share of workers with higher education	-0.06118***	-0.05212***	-0.04847***	-0.04603***
	(0.00215)	(0.00200)	(0.00196)	(0.00232)
Manufacturing or construction sector	0.03131***	0.02461***	0.01691***	0.01189***
	(0.00255)	(0.00207)	(0.00216)	(0.00255)
Change in total employment	-0.00107***	-0.00012***	-0.00008*	-0.00010***
	(0.00022)	(0.00004)	(0.00004)	(0.00003)
Share of male workers	-0.04706***	-0.03282***	-0.02917***	-0.03222***
	(0.00380)	(0.00400)	(0.00371)	(0.00456)
Constant	0.50310***	0.40296***	0.37740***	0.70386***
	(0.01162)	(0.01065)	(0.00990)	(0.01114)
Observations	86,877	71,870	57,760	44,503
R-squared	0.17	0.09	0.071	0.058

In parenthesis are std. errors clustered by municipality. ***, ** and * denote statistical significance at the 1%, 5% and 10% levels, respectively. Each model includes year and municipality fixed effects.

Table 15: Estimates after excluding 5 largest absolute changes in commuting distance

	Dependent variable is the rate of worker turnover in:			
	Year 0	Year 1	Year 2	Year 3
Relocation distance (km)	0.00035	0.00155***	0.00133*	0.00037
	(0.00025)	(0.00054)	(0.00077)	(0.0004)
Relocation indicator (=1 if relocated)	-0.00032	0.00607*	0.00558	0.00389
	(0.00323)	(0.00362)	(0.00529)	(0.00439)
Number of workers	0.00001	0.00003***	0.00003***	0.00004***
	(0.00001)	(0.00001)	(0.00001)	(0.00001)
Average experience of workers (years)	-0.01525***	-0.01243***	-0.01071***	-0.00887***
	(0.00059)	(0.0006)	(0.00059)	(0.00061)
Share of workers having children	-0.01586***	-0.03193***	-0.04330***	-0.05391***
	(0.0061)	(0.00642)	(0.00629)	(0.00733)
Average commute of workers (km)	0.00106***	0.00073***	0.00057***	0.00054***
	(0.00009)	(0.0001)	(0.00008)	(0.00009)
Share of workers with higher education	-0.06118***	-0.05212***	-0.04846***	-0.04603***
	(0.00215)	(0.002)	(0.00196)	(0.00232)
Manufacturing or construction sector	0.03131***	0.02461***	0.01691***	0.01188***
	(0.00255)	(0.00207)	(0.00216)	(0.00255)
Change in total employment	-0.00107***	-0.00012***	-0.00008*	-0.00010***
	(0.00022)	(0.00004)	(0.00004)	(0.00003)
Share of male workers	-0.04706***	-0.03282***	-0.02917***	-0.03222***
	(0.0038)	(0.004)	(0.00371)	(0.00456)
Constant	0.50315***	0.40055***	0.37747***	0.70386***
	(0.01162)	(0.01057)	(0.00989)	(0.01114)
Observations	86,877	71,870	57,760	44,503
R-squared	0.170	0.090	0.071	0.058

In parenthesis are std. errors clustered by municipality. ***, ** and * denote statistical significance at the 1%, 5% and 10% levels, respectively. Each model includes year and municipality fixed effects.

Table 16: Estimates based on a sample of firms with 15 or more workers in a year

	Dependent variable is the rate of worker turnover in:			
	Year 0	Year 1	Year 2	Year 3
Relocation distance (km)	0.00041*	0.00108***	0.00040	0.00069**
	(0.00021)	(0.00037)	(0.00046)	(0.00035)
Relocation indicator (=1 if relocated)	0.00230	0.00538	0.00670	-0.00137
	(0.00407)	(0.00363)	(0.00501)	(0.00500)
Number of employees	0.00001	0.00002***	0.00003***	0.00003***
	(0.00001)	(0.000001)	(0.00001)	(0.00001)
Average experience of workers (years)	-0.01554***	-0.01266***	-0.01052***	-0.00955***
	(0.00047)	(0.00053)	(0.00058)	(0.00068)
Number of workers having children	-0.02128***	-0.03829***	-0.04066***	-0.06327***
	(0.00698)	(0.00757)	(0.00835)	(0.00957)
Average commute of workers (km)	0.00102***	0.00075***	0.00057***	0.00048***
	(0.00013)	(0.00014)	(0.00012)	(0.00012)
Share completing higher education	-0.06369***	-0.05507***	-0.05167***	-0.04987***
	(0.00196)	(0.00202)	(0.00190)	(0.00228)
Manufacturing or construction sector	0.03356***	0.02659***	0.01865***	0.01550***
	(0.00265)	(0.00203)	(0.00198)	(0.00246)
Change in total employment	-0.00097***	-0.00010***	-0.00009**	-0.00010***
	(0.00020)	(0.00004)	(0.00004)	(0.00003)
Share of male workers	-0.05020***	-0.03694***	-0.03438***	-0.03777***
	(0.00429)	(0.00444)	(0.00411)	(0.00478)
Constant	0.51183***	0.42322***	0.35048***	0.37198***
	-0.00872	-0.01032	-0.01067	-0.01282
Observations	60,136	49,888	40,192	31,019
R-squared	0.200	0.109	0.088	0.077

In parenthesis are std. errors clustered by municipality. ***, ** and * denote statistical significance at the 1%, 5% and 10% levels, respectively. Each model includes year and municipality fixed effects.

Table 17: Estimates based on a sample of firms with 30 or more workers in a year

	Dependent variable is the rate of worker turnover in:			
	Year 0	Year 1	Year 2	Year 3
Relocation distance (km)	0.00060	0.00151***	-0.00042*	0.00057
	(0.00041)	(0.00055)	(0.00021)	(0.00043)
Dummy for relocation	0.00439	0.00104	0.00494	0.00282
	(0.00581)	(0.00568)	(0.00511)	(0.00670)
Number of employees	0.00002***	0.00001***	0.00001***	0.00002***
	(0.000001)	(0.000001)	(0.000001)	(0.000001)
Average experience of workers (years)	-0.01557***	-0.01314***	-0.01096***	-0.00865***
	(0.00062)	(0.00067)	(0.00064)	(0.00060)
Number of workers having children	-0.03292**	-0.05049***	-0.04753***	-0.05735***
	(0.01440)	(0.01751)	(0.01274)	(0.01130)
Average commute of workers (km)	0.00106***	0.00063***	0.00047***	0.00047***
	(0.00018)	(0.00016)	(0.00016)	(0.00015)
Share completing higher education	-0.07261***	-0.06395***	-0.06107***	-0.05872***
	(0.00270)	(0.00296)	(0.00312)	(0.00336)
Manufacturing or construction sector	0.02920***	0.02234***	0.01395***	0.01321***
	(0.00338)	(0.00325)	(0.00334)	(0.00397)
Change in total employment	-0.00093***	-0.00011***	-0.00001	-0.00005*
	(0.00010)	(0.00002)	(0.00002)	(0.00003)
Share of male workers	-0.05026***	-0.03273***	-0.03109***	-0.03594***
	(0.00578)	(0.00638)	(0.00751)	(0.00829)
Constant	0.47880***	0.39555***	0.38369***	0.29378***
	(0.01247)	(0.01401)	(0.01266)	(0.01187)
Observations	29,012	24,139	19,497	15,075
R-squared	0.262	0.140	0.117	0.102

In parenthesis are std. errors clustered by municipality. ***, ** and * denote statistical significance at the 1%, 5% and 10% levels, respectively. Each model includes year and municipality fixed effects.

DTU Transport performs research and provides education on traffic and transport planning. It advises the Danish Ministry of Transport on infrastructure, economic appraisals, transport policy and road safety and collects data on the transport habits of the population. DTU Transport collaborates with companies on such topics as logistics, public transport and intelligent transport systems.

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